On The Detection and Monitoring of Invasive Exotic Conifers in New Zealand using Remote Sensing

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I dedicate this thesis to my beautiful wife, my loving parents, and my ever-loyal dog.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this thesis are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

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Abstract

Conifers are amongst the most economically and culturally valued trees on Earth. They provide significant ecosystem services both within and outside of their natural range. For this reason, many northern hemisphere conifer species have been planted extensively in southern hemisphere countries. The evolutionary history of many conifer species means that they are frequently invasive in indigenous ecosystems. In New Zealand large areas of northern hemisphere conifers have been planted. These areas include commercial plantations managed for timber production and areas established for erosion control, hydrology management, agricultural, and amenity purposes. Many historical introductions were inappropriately located and included conifer species that are now known as invasive. This resulted in exotic trees with vigourous growth, rapid maturity, and abundant seed production occurring in remote and mountainous areas from where they have spread. The land area now invaded by exotic conifers is estimated to total around 2,000,000 ha and is increasing even under current management. The ecological and social impact of this situation is great, and this has led New Zealand government agencies, and other organisations, to undertake substantial control programmes. Without these efforts a much larger area will be invaded leaving a substantial detrimental legacy. Invasive conifer control relies on herbicide application or mechanical removal. These methods are expensive and challenging particularly when conducted across large areas of frequently mountainous terrain. Accurate information on the location of invasive conifers is either not currently available or is inadequate.

Remote sensing surveys potentially offer a useful solution as they can provide valuable information across large areas of challenging terrain and can deliver detailed information about targeted areas. With appropriate research remote sensing methods could provide valuable information to help improve the efficacy and efficiency of invasive conifer control programmes.

There has been substantial research into the remote detection of invasive plants originating from many parts of the world. Space-borne and both piloted and unpiloted airborne platforms have been used. In many instances this has provided useful and practical information for managers and policy makers but, to date, research into remote detection of invasive conifers has been limited in scope, incomplete, or restricted to a single environment. Furthermore, a comprehensive review of the research literature revealed several gaps that the experimental research contained within this thesis addressed. Two of the research topics used the emerging technology of unpiloted aerial vehicles (UAVs). These flexible and reliable platforms provide a new data source that can provide ultra-high-resolution data over small to medium sized areas. With appropriate method development this represents a new source of critical information on the early stages of invasive conifer spread where detecting small plants is critical. The technology has delivered substantial efficiency compared to conventional ground-based measurements but has ushered in a new sampling challenge where the operator must decide how to deploy the UAV for data collection. This is particularly relevant where efficient re-use of UAV-based models is desirable to save model development and reference data labelling effort. The challenge of monitoring historic trends in invasive conifer spread was also investigated through analysis of the Landsat archive. No previous research had addressed this topic although automated methods developed for other applications had considerable promise. Single-date analysis can only provide information on the current distribution of invasive conifers and so the impacts of historical policy and management activities remain anecdotal without considering the temporal dimension.

Given the knowledge gaps identified in the published literature three broad research questions were developed and addressed through experimentation.

1. Can ultra-high-resolution data be used to detect the presence of invasive exotic conifers prior to the onset of early coning in a highly vulnerable environment?

2. Can UAV-based models of invasive conifer distribution be transferred between sites and does site complexity have a significant effect on model portability?

3. Given the size and availability of the Landsat archive can automated methods be developed that allow tracking of the historical spread and management of invasive conifers?

Three experiments were implemented to address these three research questions. To address research question one a detailed field study was installed in a vulnerable environment with a simplistic grassland non-target vegetation structure. The study site was subject to a first order conifer invasion event spreading from a shelter-belt on agricultural land. Very high-resolution multispectral and laser scanning data was collected over the site using both UAV and conventional piloted aircraft. These data were used to develop statistical models suitable for detecting invasive conifers based on their spectral and structural properties. A large field dataset (ca. 17,000 trees) was also collected and used to validate the accuracy of the remote detection methods. Detection errors were characterised with reference to the size, age, and coning status of trees measured at the study site.

To address research question two a multi-site case study that encompassed an ecological and site complexity gradient of the vulnerable ecosystems within New Zealand was installed. Across all sites UAV-based models of invasive conifer distributions were developed. These were transferred to all other areas of interest (AOI) within the experimental framework. The experimental design meant that the portability of models both within, and between, sites could be tested. The influence of the complexity of both the donor and receiver site on model predictive accuracy after transfer was also explored. In all cases model accuracy was assessed using cross-validation.

To address research question three a methodology was developed based on an implementation of a land cover change tracking algorithm within Google Earth Engine. This technique was applied to a vast and heterogeneous mountainous area of New Zealand's South Island. The algorithm was carefully configured to identify changes in the pixel-level spectral trajectory within the Landsat archive that might be associated with invasive conifer spread or management control. These change segments were treated as base learners in a subsequent random forest attribution model that defined the causal agent of identified changes in the landscape.

The main findings of the research were as follows.

1. Ultra-high-resolution data was extremely useful for the early detection of invasive conifer invasions including small trees. Critically relatively simple statistical methods were suitable for the detection of 99% of all trees found to be coning.

2. UAV-based invasive conifer distribution models were found to be robust to transfer to different AOIs within the same site without a decrease in accuracy. UAV-based invasive conifer distribution models could be transferred to sites with similar or lower complexity than the sites used for model development without a significant decrease in accuracy. However, models transferred to more complex sites could not produce viable results. Invasive conifer models based on spectral data were found to be more robust to transfer than those based on ALS data.

3. The methodology implemented offered a viable means of detecting vegetation changes over time through the Landsat archive. The attribution models developed

had moderate accuracy but substantial class confusion remained. Nevertheless, maps of invasive conifer spread and control for the period 2000 - 2019 could be produced and were accurate enough to be useful for assessing the impact of historical management and land use policy within the expansive study area.

This research has shown that through exploiting a range of different platforms remote sensing can provide critical information for the detection and monitoring of invasive conifers across a wide range of vulnerable environments. Through matching the platform and sensor to the desired application practitioners can acquire accurate information that operates from the sub-tree scale up to the regional or national scale. New knowledge on the portability of UAV-based invasive conifer distribution models has been produced with clear findings that will increase sampling efficiency, and offer guidance for practitioners on when models can be reused and when new training and model development data is required. The most comprehensive systematic review on the use of an emerging remote sensing technology (UAVs) for invasive alien plant detection was also produced. This review has highlighted trends in the current research, research gaps, and offered guidance on future development pathways that must be followed to increase the value that can be extracted from these datasets.

Publications

The following articles have been produced from the research presented in this thesis. These are either published or are currently undergoing peer-review at the time of submission.

i Dash, J.P., Watt, M.S., Morgenroth, J., Paul, T.S.H., Hartley, R. (2019) Taking a closer look at invasive alien plant research: A review of the current state, opportunities, and future directions for UAVs. Methods in Ecology and Evolution https://doi.org/10.1111/2041-210X.13296

ii Dash, J.P., Watt, M.S., Paul, T.S.H., Morgenroth, J., Pearse, G.D. (2019) Early Detection of Invasive Exotic Trees Using UAV and piloted Aircraft Multispectral and LiDAR Data. Remote Sensing 11 (15) https://doi.org/10.3390/rs11151812

iii Dash, J.P., Paul, T.S.H, Morgenroth, J., Watt, M.S. (2020) Transferability of UAV based models for invasive conifer mapping within and between sites across a site complexity gradient. **In review**.

iv Dash, J.P., Paul, T.S.H., Morgenroth, J., Watt, M.S. (2020). Tracking *Pinaceae* invasions and their management in New Zealand's high country using time-series Landsat imagery (2000 - 2019) and the LandTrendR algorithm. **In review**.

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Nomenclature

Acronyms / Abbreviations

ABA Area based approach

AIC Akaiake information criterion

ALS Airborne laser scanning

ANN Artificial neural network

AOI Area of interest

ASTER Advanced Spaceborne Thermal Emission and Reflection Radiometer

AUC Area under the receiver operator curve

AWiFS Advanced Wide Field Sensor

B Blue

BIC Bayesian information criterion

CA Cellular automata

CAO Carnegie Airborne Observatory

CHM Canopy height model

CMA LCraigieburn Management Area

CNN Convolutional neural network

CRSDA China Centre for Resources Satellite Data and Application

DTM Digital terrain model

EO-1 NASA's Earth Observation 1 satellite

ESA European Space Agency

ETM Enhanced Thematic Mapper

EVI Enhanced vegetation index

FSC Forest Stewardship Council

G Green

GAM Generalised additive model

GARP Genetic algorthm for rule set production

GDAL Geographical data abstraction library

GEE Google Earth Engine

GIS Geographical information system

GLCM Grey level correlation matrix

GLM Generalised linear model

GNSS Global navigational satellite system

GPS Global Positioning System

GSD Ground surface distance

HFP Hanmer Forest Park study site

IAP Invasive alien plant

ICMA Invasive conifer management area

IMU Inertial measurement unit

InSAR Interferometric synthetic-aperture radar

IR Infrared

ITA Individual tree analysis

kappa Cohen's kappa coefficient

KFP Kaweka Forest Park study site

LandTrendR Landsat-based detection of trends in disturbance and recovery

LCDB Land cover database

Lidar Light detection and ranging

LINZ Land Information New Zealand

LMM Linear mixed models

LOOCV Leave one out cross validation

LP The Lake Pukaki study site

LR Logistic regression

LT-GEE The Google Earth Engine implementation of the LandTrendR algorithm

MESMA Multiple Endmember Spectral Mixture Analysis

MNF Minimum noise fraction

MODIS Moderate resolution imaging spectroradiometer

MP Mega pixel

MSS Multispectral Scanner - Landsat instrument

MTMF Mixture tuned match filtering

NAIP National Agriculture Imagery Program

NASA Nation Aeronautics and Space Administration

NBR Normalised burn ratio

NDVI Normalised difference vegetation index

NIR Near-infrared

OA Overall accuracy

OBIA Object-based image analysis

OLI Operational Land Imager

OOB Out of bag

PA Producer's accuracy

PRF Pulse repetition frequency

R R statistical computing environment

R Red

RE Red edge

RENDVI Red edge normalised difference vegetation index

RF The Random Forests algorithm

ROC Receiver operator curve

RQ Research question

SAHM Software for assisted habitat mapping

SAM Spectral Angle Mapper

SAVI Soil adjusted vegetation index

SfM Structure from motion

SPOT Satellite Pour l'Observation de la Terre

SVM Support vector machines

TC Tasselled-cap

TCB Tasselled-cap brightness

TCG Tasselled-cap greenesss

TCW Tasselled-cap wetness

TM Thematic Mapper

TSS True skill statistic

UA User's accuracy

UAV Unpiloted aerial vehicle

UAV-LS Airborne laser scanning data collected from a UAV

USGS United States Geological Survey

VI Vegetation index

VSWIR Visible to short wave infrared

WEKA Waikato Environment for Knowledge Analysis

WV2 WorldView-2

Chapter 1

Introduction

This chapter establishes the context for the research presented within this thesis, outlines the objectives, and frames the impact of the research. The burgeoning issue of invasive conifer spread in New Zealand, the consequences of the situation, and research and practical measures that are underway to mitigate them are also covered. The structure of this thesis is presented with reference to the key research questions.

1.1 Rationale

Human life and economic activity is sustained by the Earth's ecosystems. Trees are amongst the most important constituents of these systems delivering many crucial ecosystem services that support our way of life. These services include provisioning of timber, fibre, and fuel, regulation of climate and ecosystem process, and protection, through soil stabilisation and water and nutrient cycling (Castro-Diez et al., 2019; MacDicken, 2015). Trees also provide substantial cultural values for the majority of human societies (Mason et al., 2017). As the human population has expanded and spread to cover most of the planet the demand for these services has increased and this has led to the global distribution of many species whose evolutionary history means that they can efficiently provide these services (Castro-Diez et al., 2019).

Conifers are amongst the most economically important tree species on Earth forming the basis of major forest industries, and providing a significant proportion of the total annual timber yield (Mead, 2013). In the northern hemisphere, a small number of conifer species are the dominant vegetation over the vast boreal areas. This notably includes the Taiga, the world's largest terrestrial biome, covering extensive areas of Asia, Europe, and North America (Farjon and Farjon, 2008). In the southern hemisphere, plantation grown conifers of northern origin form the foundation of the softwood forest industries in New Zealand, Australia, Chile, and South Africa. Here they confer substantial economic, environmental, and societal benefits. In New Zealand, the planted forest sector is founded on exotic conifers, and has developed to become a cornerstone of the nation's economy. The sector generates $4.74 billion per annum in export revenue, and directly employs around 26,000 people (NZFOA, 2016). In addition to commercial plantations established for timber production, conifer forests have also been established for erosion control and for amenity value.

Several exotic conifer species have become invasive, and in certain settings have started invading indigenous and semi-indigenous vegetation. Invasive conifers, also referred to locally as 'wilding conifers' or 'wilding pines', have become dominantly invasive in grasslands and shrublands across large areas (Howell and McAlpine, 2016; Ledgard, 2009). The area affected by invasive conifers is approximated to be 2,000,000 ha. This area is larger than the national plantation estate in New Zealand, and is thought to be increasing at 5-6 % per year (Anon., 2011).

Despite its geographic isolation and relatively recent history of human settlement the presence of invasive conifers, alongside the considerable impact of horticultural and agricultural plants, has led to New Zealand having amongst the highest levels of invasive exotic plants in the world (Turbelin et al., 2017). The economic and ecological costs of this are considerable, and to control, or at least slow, their spread detection and eradication measures are required. A range of chemical and physical control methods are available, but to be effective these require accurate detection methods so that control can be targeted.

Eradication efforts often require the identification of juvenile trees before the onset of seed production. This significantly complicates the task because detection success is often dependent on the density of the infestation, size of the individuals present, and the complexity of the terrain and vegetation structure in the area of interest (Andrew and Ustin, 2008). Current surveillance and monitoring methods rely on conifer detection across large areas using helicopter-based surveys by skilled operators (Woods, 2003), ground surveys in very small areas, or combinations of both (Cochrane and Grove, 2013). Detection success using current approaches is highly variable and the lack of an effective method for detection of invasive conifers in New Zealand is a major hindrance to the development of effective control procedures.

Remote sensing potentially provides a means for accurate invasive conifer detection over large areas with varied terrain and vegetation types. These technologies have been widely used to detect and monitor invasive plants in a variety of environments (Hall and Asner, 2007; Hestir et al., 2008; Mureriwa et al., 2015; Underwood et al., 2003). However, research into detection and monitoring of invasive conifers is limited. Recent research developed a method for invasive conifer detection by classifying airborne laser scanning (ALS) pulse returns originating in invasive conifers. This approach relies on combining airborne ALS data with aerial imagery (Dash et al., 2017a). However, these results are only applicable to a single vulnerable habitat type and sensor configuration, and further research is required to develop methods for other areas and sensor types. A body of relevant research comes from the boundary of the boreal and Arctic ecotones (Hantson et al., 2012; Næsset and Nelson, 2007; Rees, 2007; Stumberg et al., 2014a, 2013; Thieme et al., 2011) where there is considerable interest in monitoring changes to the tree line that are associated with climate change. However, there are significant differences in environmental conditions and vegetation composition between Scandinavia and New Zealand and so specialised techniques must be developed. In particular, the Scandinavian research targets detection of all trees in the area of interest. This is unsuitable in New Zealand as detection techniques must differentiate invasive conifers from non-target trees and shrubs. This PhD research will comprehensively review and develop invasive conifer detection methods in a range of vulnerable environments across New Zealand.

The proliferation of remote sensing data sources and analytical methods in recent years means that there is an abundance of candidates available to stakeholders for detection and monitoring (Bradley, 2014; Huang and Asner, 2009). The most combination of platform and sensor is dependent on the properties of the target plant, the properties of non-target vegetation present, and the complexity of the area of interest (AOI). Furthermore, the choice of sensor and platform that best suits a specific use-case is dependent on the intended application and acceptable error rates. It is clear that no single sensor and platform combination can fulfil the full range of information requirements. The applications of remote sensing of invasive plants are numerous and varied, this means that a range of sensor and platform combinations are required to provide adequate data (Figure 1.1). At the broadest scale stakeholders require information that can inform on the global and regional distribution of invasive alien plants (IAP) (Turbelin et al., 2017). The broad coverage available from Earth observing missions such as NASA's Landsat and the European Space Agency's (ESA) Copernicus mission can fill this niche. At regional and national scales government organisations require information on the location and spread of IAPs to allocate limited resources towards the most effective control and management strategies (Figure 1.1). These requirements can be served from space-borne satellites but also through a patch work of surveys from conventional manned aircraft. At the estate level managers charged with IAP management can also make use of data from both of these platforms with various sensor configurations. Finer resolution data also has an important role to play. This can be provided both from modern sensors on conventional aircraft and from the emerging solutions offered by unpiloted aerial vehicles (UAV). These platforms and the integrated miniaturised sensors offer data at a finer spatial and temporal resolution than ever before. This means that, if appropriate methods can be developed, new information can be provided to reveal IAP spread at the earliest opportunity and to offer rapid assessments of the efficacy of control methods such as herbicide control (Figure 1.1). The range of stakeholder information demands, and variety of remote sensing tools indicates that a range of research is required to deliver the benefits of each. The application of single date imagery derived detection of invasive plants is well established and conventional aircraft and satellite borne sensors are operational tools in many instances. The focus of this thesis was the novel remote sensing platform of UAVs and attempting to automate extraction of useful time series information from long-lived Earth observation archives.

The rapid advancement and proliferation of UAVs in the past five years means that the UAV sector has now matured to offer a flexible and reliable data capture solution that can fill an important niche in invasive conifer detection and monitoring. Range limitations caused by battery life and legislative restrictions hamper the uptake of UAVs for operational purposes over large areas. However, the high-resolution data offered means that these platforms can overcome several limitations that have traditionally hampered remote sensing studies targeting IAPs (Dash et al., 2019b). As the sophistication of the miniaturised sensors they carry improve and become

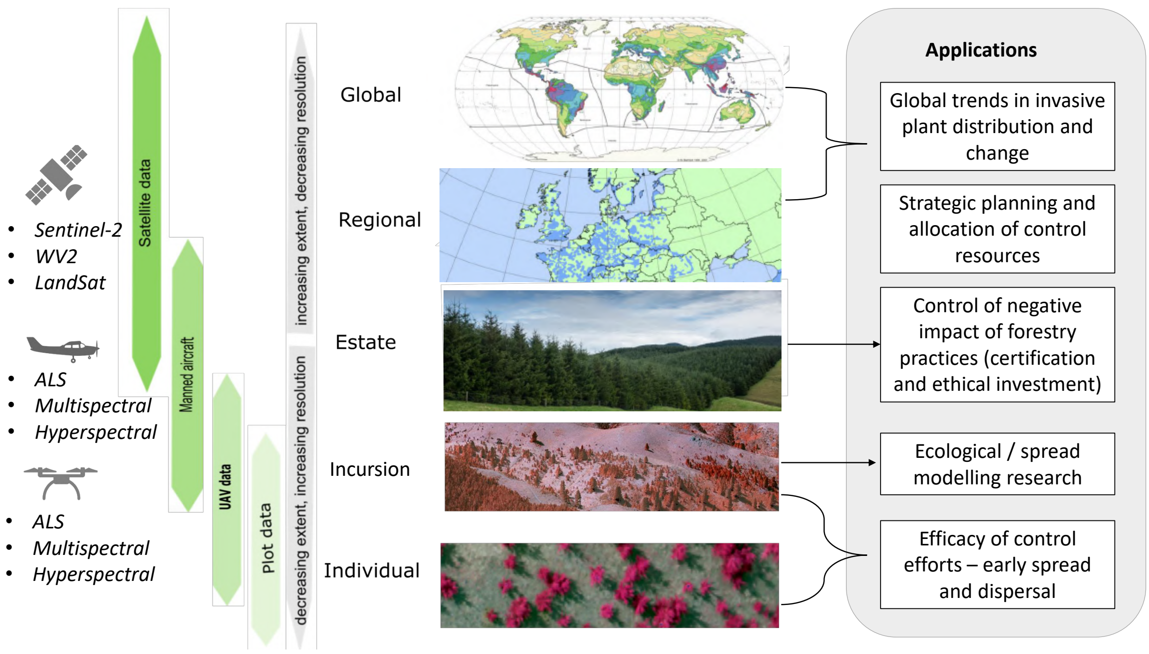

Fig. 1.1 The various data sources, scales, and applications of remote sensing data in the context of invasive alien plant research.

more affordable (Heaphy et al., 2017) they will provide an increasingly important data source. Relevant use cases include detection of very small plants prior to the onset of reproductive maturity as this is critical to the prevention of further spread into new areas (Dash et al., 2019c; Nunez et al., 2017). As the technical capability of UAV-borne sensors improves other opportunities emerge such as the detection of physiological changes associated with herbicide application using hyperspectral data which can inform control activities by providing early indication of successful control (Scholten et al., 2019).

The widespread availability of UAVs to researchers and land managers offers a valuable new data source but also presents a novel sampling problem. The practitioner is faced with a decision about how best to deploy UAV for data collection when total coverage is frequently impossible. Furthermore, the models developed for automated detection of a target object require a labelled reference dataset. This dataset can be difficult and expensive to collect and model development requires expert input and can be time-consuming. This means that the possibility of re-using models developed in one area in another area is appealing. However, no research has addressed this topic and therefore no guidance is available to practitioners about when this approach is feasible. In this thesis this gap in the research was addressed through a multi-site experiment that encompasses the full complexity range of vulnerable sites within New Zealand.

Regardless of the sensor and platform configuration single date remote sensing can only inform the current status and distribution of invasive alien trees. In contrast, time series imagery from long-lived space-borne missions can reveal both abrupt and gradual historic trends (Vogelmann et al., 2016). The invasive nature of some exotic conifers has been noted in New Zealand since the 1960s (Benecke, 1967) and efforts to control their spread have been underway since around the year 2000. However, information on the rates of spread and the efficacy of control methods applied is absent or anecdotal. This is a significant gap in the knowledge required to tackle the issue of invasive conifers. Detailed quantitative knowledge of historical spread patterns will deepen our understanding of spread rates and the mechanisms that facilitate dispersal to and invasion of new habitats. This will be critical for identifying areas with high ecological or social value that are particularly vulnerable and allow stakeholders to plan control efforts accordingly. Understanding the spatial patterns of invasive conifer control success rates following historical management activity will help identify success rates for different strategies. Given the limited resources available for both research and practical management activities this should provide a valuable dataset to help optimally allocate funding based on past activities. The advent of open access to the Landsat archive means that with appropriate method development it may be possible to use the spectral trajectories of the time-series stack to identify historical spread rates and control activities. Given the vast size of the archive this requires automated methods for change detection and a high-performance computing facility to extract and process the data. In this thesis recent algorithm developments and computing infrastructure are explored for this purpose.

1.2 Primary research questions

The research presented in this thesis contributes to the existing understanding and aims to fill specific gaps in the research knowledge about the detection and monitoring of invasive conifers using remote sensing. These study areas were identified through a comprehensive summary of contemporary knowledge on the topic and engagement with stakeholders. Once knowledge gaps were identified a series of research questions were developed and investigative case studies were established to provide data to answer these questions. The case studies installed were designed to develop novel techniques for detecting and monitoring invasive conifers in New Zealand conditions.

Given the knowledge gaps identified in the published literature three broad research questions (RQ) were developed and addressed through experimentation.

1. Can ultra-high-resolution data be used to detect the presence of invasive exotic conifers prior to the onset of early coning in a highly vulnerable environment?

2. Can UAV-based models of invasive conifer distribution be transferred between sites and does site complexity have a significant effect on model portability?

3. Given the size and availability of the Landsat archive can automated methods be developed that allow tracking of the historical spread and management of invasive conifers?

The primary objective of this research was to provide a means of identifying and monitoring invasive conifers at a range of geographic scales and to meet the information requirements of various stakeholders with numerous objectives. As no single solution can meet all the information requirements a range of different sensor and platform configurations have been deployed and methods specifically developed designed to fill information gaps identified in the research literature and through discussion with experts and stakeholders.

1.3 Thesis structure

This thesis comprises seven chapters. Chapter one provides a general introduction to the thesis topics and describes the background, objectives, and motivation for the studies. Chapter two contains a detailed literature review on the detection and monitoring of invasive plants using remote sensing methods and was designed to identify trends and gaps in the research and was used to guide the development of the research questions presented in the previous section. The focus of chapter three was the emerging field of UAV remote sensing. The review in this chapter systematically summarised the entirety of published research relating to the use of this important technology for the detection and monitoring of invasive plants. This was necessary as the initial literature search (chapter two) showed that this specific area had not been subjected to a comprehensive review. In this manner, the existing knowledge was summarised and published providing a new resource for the research community and aiding development of the thesis research questions. The next three chapters present the results of experimental case studies installed to provide data for this thesis to address the research questions developed to fill the gaps identified in chapter two and three.

The research presented in chapter four was designed to provide evidence to address research question one (RQ1). A study was designed and installed to develop and test methods aimed at very early identification of invasive conifer invasions in a vulnerable grassland dominated environment. This study used datasets collected from both UAV and conventional piloted aircraft as the capacity of ultra-high resolution data, rather than the platform, was or primary interest and in recognition of the current limitations to UAV datasets identified in chapter three.

In chapter five the results of a comprehensive multi-site experiment addressing the portability of UAV-based invasive conifer distribution models and designed to address RQ2 is presented. Evidence to answer this RQ was acquired through developing, testing, and transferring invasive conifer distribution models to environments with conditions that varied from those of the site used for model development. This carefully designed experiment encompassed an extensive range of vulnerable environments within New Zealand and also represented a site complexity gradient according to the definitions of site complexity identified through the literature review in chapter two (Andrew and Ustin, 2008). Model transfer both within and in between sites was examined and the influence of the complexity of both the donor area of interest (AOI), used for model development, and the receiver AOI, to which the model was transferred, were investigated.

The study presented in chapter six was designed to provide evidence to address RQ3. This study used a very different scale and resolution of data and presented the development of a method that could exploit the extensive Landsat time series archive. A suitable algorithm and computing platform were identified, parameterised, and implemented to automate the detection of land cover changes across the entirety of a large and heterogeneous study area within New Zealand's South Island containing significant areas of invasive conifer infestation and related control. In a subsequent modelling step, methods were developed to attribute the causal agent of the land cover changes identified to test whether changes associated with historic invasive conifer spread and control across a relevant time period could be accurately identified.

Finally, chapter seven provides a synopsis of the main findings relating to the three RQs, clearly identified the limitations of the research presented, and suggested possible future directions for further research.

Chapter 2

Literature review on remote detection and monitoring of invasive plants

In this chapter I have provided a review of the relevant literature related to invasive plant detection using all forms of remote sensing. The objective of this review was to summarise the current state of knowledge on the detection of invasive plants, and to help identify suitable technologies, data sets, and analytical techniques.

2.1 Invasive plants

The prevalence of invasions by non-native invasive plants has considerable consequences in many environments and is a significant, and increasing, challenge for land managers (Richardson et al., 2014) and for society more broadly (Castro-Diez et al., 2019; Early et al., 2016). This is particularly true in mountainous areas where climate change and increased human activity are making significant impact. Increased levels of anthropogenic disturbance coupled with a changing climate are expected to trigger an increase in the abundance of invasive plants, and an upward expansion of exotic invasive species in vulnerable mountainous regions (Dainese et al., 2017). Recent research in the European Alps has found that non-native plants are shifting upwards at approximately twice the rate as native plants (Dainese et al., 2017). This is partly facilitated by the bias towards invasive characteristics in non-native species that are typically associated with characteristics that are favourable for human applications. Both native and non-native plants appear to be migrating faster than the current velocity of climate induced change. This is thought to be due to the prevalence of long-distance dispersal events, and the growing road network. However, the higher velocity spread of non-native plants, compared with natives, means that the probability of replacement of native species in new climatic niches and disturbed areas is high. This may lead to dramatic changes in vegetation structure in areas such as the European Alps with ongoing anthropogenic climate change (Dainese et al., 2017).

Historically, trees did not feature prominently in global lists of important invasive plants (Richardson et al., 2014), but more recently the invasive and unfavourable nature of many tree species has been recognised (Rejmánek, 2014; Rejmánek and Richardson, 2013; Richardson and Rejmanek, 2011). Now, many tree species are included in databases of the most widespread and damaging plants (Richardson and Rejmanek, 2011). These trees have the potential to cause significant threats to biodiversity and ecosystem function, as well as significant provisioning of fuel, fibre, and food sources in many cases. The prevalence of invasive trees has been caused by human intervention for forestry, agroforestry, and ornamental purposes. The resulting propagule pressure, combined with increased disturbance rates, is resulting in significant invasions from tree species in many parts of the world (Richardson et al., 2014). The long time lag associated with tree development compared to other plant types is probably responsible for the initial misplaced belief that trees represented a less significant threat

(Kowarik and Kowarik, 1995). In response to the emerging recognition of the invasive nature of trees forest certification such as the Forest Stewardship Council (FSC) now require that the negative externalities of invasions associated with forest plantations are considered. It is highly likely that this trend will continue in the future with ever stricter environmental restrictions enforced by certification bodies (Wilgen and Richardson, 2014).

The spread of invasive trees is strongly associated with human migration, colonisation, and trade. Using databases of invasive trees and their source countries a global donor-acceptor network has been produced (Figure 2.1) (Richardson et al., 2014). This figure clearly shows three main sources of invasive trees that are significant for New Zealand, and these are undoubtedly associated with the rise of plantation forestry. Trees from Europe, North America, and Australia are the significant invasive species here. These three donor regions can be explained as a significant source of New Zealand's migratory origins, the source of its plantation forestry species, and its nearest neighbour respectively. Eliminating invasive trees from some environments in New Zealand may be infeasible because the economic and environment cost would be unacceptably high. However, through a careful consideration of each species characteristics during planting, and highly targeted control programmes in specific areas there is a possibility that the most harmful aspects of invasive trees can be mitigated.

2.2 Conifer ecology

Conifers include the most economically important tree species on Earth forming the basis of major forest industries, and contributing significantly to the total annual timber consumption (Mead, 2013). Conifers' natural range covers areas on all continents, except Antarctica, and they have been widely propagated beyond this range by foresters throughout the world due to their commercial value (Farjon and Farjon, 2008). In the

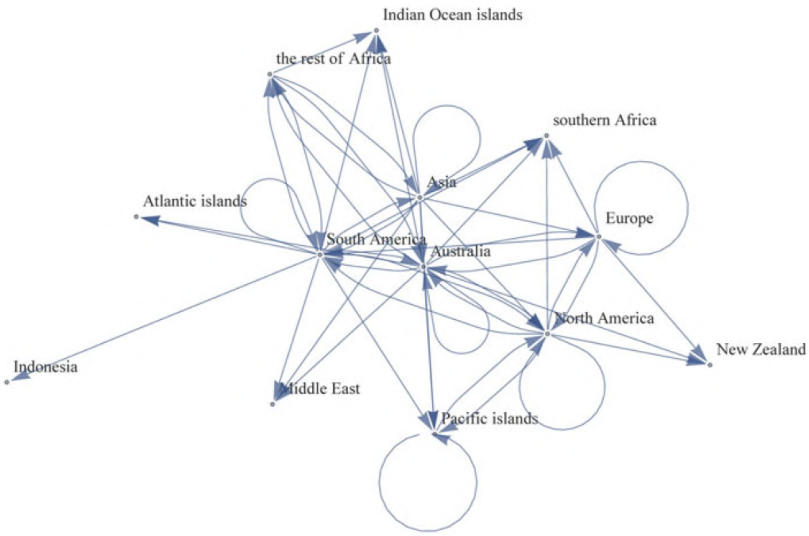

Fig. 2.1 The global donor–acceptor network of invasive alien trees. Arrows indicate that a donor region has contributed more than five invasive species to an acceptor region. South America also includes Caribbean islands and Central America. Regions on the outside of the figure play a minor role (or no role) as donors, whereas those towards the centre of the figure are major donors. Source (Dainese et al., 2017) based on data from (Rejmánek, 2014)

northern hemisphere a small number of conifer species are the dominant vegetation over vast boreal areas. This notably includes the Taiga, the world's largest terrestrial biome, covering extensive areas of Asia, Europe, and North America. Conifer distribution and diversity have been strongly defined by patterns of glaciation during the last ice age and continental drift. Many conifer species have evolved to exploit niches that are not ideally suited to plant growth where they can out-compete angiosperms due to their evolutionary strategies. Unfortunately, this makes them highly invasive in some environments. Present day conifer diversity hot spots encircle the Pacific Ocean where they are present in all vegetation layers. Many species have evolved to become amongst the tallest trees on Earth and dominate the canopy layer in many regions (Farjon and Farjon, 2008).

In the southern hemisphere, plantation grown conifers form the foundation of the softwood forest industries in New Zealand, Australia, Chile, and South Africa, providing substantial economic and social benefits (Yao et al., 2014). Notable economically important species include *Pinus radiata* (D.Don) (*P. radiata*) and *Pseudotsuga menziesii* (Mirb) (*Ps.Menz*). There are also a significant number of remnant species that are not economically important, and are rarely planted, but represent a significant invasion risk due to their evolutionary ecology. Many of these species have evolved as pioneers that can efficiently populate ecological niches in disturbed landscapes and can become locally dominant. These traits mean that when translocated to a new environment they frequently invade many habitat types, and out compete native vegetation. This is particularly apparent following disturbance events that can leave many habitats increasingly vulnerable to invasion.

2.2.1 Invasive conifers in New Zealand

The natural regeneration of introduced conifers in New Zealand was first recorded in the late 1800s when the considerable seed production of conifers in the genera *Pinus*, *Picea*, *Abies*, and *Cupressus* were observed (Smith, 1903). By 1925, several species of introduced conifers were noted to be reproducing freely throughout New Zealand (Cheesman, 1925). This led to a marked increase in area affected by exotic conifers from the late 1940s (Hunter and Douglas, 1984) thought to be associated with reduced land management by burning and a decline in grazing pressure in many areas (Benecke, 1967; Gibson, 1988; Ledgard, 2003). Negative perceptions of invasive conifer spread first emerged following *Pinus contorta* invasions of large areas of the Central North Island in the 1960s, including areas of the Tongariro National Park (Cooper and Mazey, 1984; Ledgard, 2003; Wadrop, 1964). In the following decades, concerns over the negative impact of invasive conifer spread increased and this ultimately led to the inception of several research studies on the topic, as well as, the development of spread mitigation and control guidance relating to invasive conifers (Ledgard and Langer, 1999).

Ten species are thought to be invasive conifers in New Zealand (Table 2.1) (Howell, 2019). Of the recognised invasive species only *P. radiata* and *Ps. menz* are commercially important and still planted as part of industrial forestry. Gene editing technologies are currently being developed to breed sterile *Ps. menz* trees within New Zealand and its persistence as a commercial tree species may depend on this technology. However, these developments will not affect trees that are already present in the landscape, and so detection techniques are urgently required to target eradication efforts. Although *P. radiata* is included in Table 2.1 and is considered invasive the weed potential of this species is considerably lower.

Table 2.1 Invasive conifers in New Zealand ordered by their spreading vigour (source: (Ledgard and Langer, 1999))

Species	Age of significant coning (y)*
Pinus contorta	8
Pinus sylvestris	12
Pinus mugo	8
Pseudotsuga menziesii	12
Pinus nigra	13
Larix decidua	12
Pinus ponderosa	13
Pinus muricata	13
Pinus pinaster	10
Pinus radiata	10

1

The current distribution of invasive conifer infested land in New Zealand is not well described, but is estimated to total approximately 2,000,000 ha, and to be increasing in many areas (Froude, 2011). The properties of affected land range from exceptionally dense infestations of a single species covering large areas, to individual trees present at densities as low as one tree per many hectares. The costs from lost pastureland alone are estimated at between $88 to $221 million (Velarde et al., 2015), and these costs would be significantly higher if the loss in natural capital caused by disruption of indigenous ecosystems could be accounted for (Froude, 2011).

Extensive close canopy stands of mature invasive conifers are relatively easy to detect across the landscape although smaller groups and isolated individuals of various size and particularly juvenile and stunted trees are more problematic. The control of early invasion stages, characterised by smaller, juvenile, and more scattered trees, is the most cost-effective way to prevent further expansion of conifer infestations (Froude, 2011; Ledgard and Paul, 2008). The detection of such trees is critical for invasive conifer management, even if the detection of individuals at such an early stage of invasion is a complex and laborious task (Clifford et al., 2013; Ledgard and Paul, 2008).

2.3 Remote Sensing Technologies

The purpose of remote sensing is to infer the properties, or condition, of an object without making physical contact with it (Asrar, 1989). Since its development remote sensing has made a profound impact on natural resource management. This is a rapidly advancing research area with an abundance of new sensor, positioning, and sensor platform technologies regularly emerging. Sensors can be deployed on the ground for detailed local-scale observations (e.g. terrestrial laser scanning) but in most instances, they are mounted on an airborne or extra-planetary orbital platform to observe objects on the Earth's surface or the Earth itself. Two of the most important characteristics that describe the functionality of a sensor are its resolution and energy source, these characteristics can be used to separate remote sensing studies. In the following sections some details on the most relevant technologies for invasive conifer detection are summarised. In this literature review the discussion is divided between systems that are passive (solar illuminated e.g. satellite imagery) and those that actively provide their own energy source (e.g. ALS, radar) (Huang and Asner, 2009).

2.3.1 Airborne laser scanning

Airborne laser scanning (ALS) is an active remote sensing technology that uses the distance measurement technique light detection and ranging (Lidar) to infer the range between the sensor and a distant target. ALS systems typically consist of a laser scanner and sensor unit mounted on an aircraft. The system emits pulses of light, typically in the near-infrared (1064 nm), and infers the range to a remote target object through accurately measuring the time elapsed before backscattered light from the target is returned. An inertial measurement unit (IMU) and global navigational satellite system (GNSS) on board the aircraft provide exact positional information that allows each return to be converted into a 3D coordinate (i.e. longitude, latitude, and elevation) (Dash et al., 2016a).

The resulting data set of dense positional information on the distant target is referred to as a point cloud. Many systems emit more than 200,000 pulses per second and can record multiple discrete returns per pulse. This abundance of data means that ALS derived point clouds provide an exceptionally detailed 3D representation of vegetation structure, and the terrain below it. In vegetated areas, a proportion of the emitted laser pulses typically penetrates all vegetation and is back scattered to the sensor from the ground below. Once separated from the vegetation returns the ground points can be used to produce a digital terrain model (DTM) usually via triangulation. These models provide the most detailed description of the forest floor available, resulting in useful information on slope, aspect, and hydrological conditions. The DTM can be used to convert the elevation of the vegetation point clouds into locally normalised heights. The above ground point cloud can then be used to produce a canopy height model (CHM), and interrogated to produce meaningful metrics that contain useful information about vegetation structure (Dash et al., 2016a). Data from ALS are typically separated into campaigns that digitise the entire return profile of the laser pulse recorded by the sensor (full waveform), and those that record discrete returns, or echoes, from the back scattered light when the return intensity is greater than some pre-defined threshold (discrete). Most research uses discrete ALS data with the full waveform datasets only beginning to be researched and exploited in the context of exotic plant detection.

When combined with ground measurements, metrics derived from discrete ALS point clouds can improve the detail and quality of forest resource description. Using area based techniques ALS data has been developed into a powerful, and practical, tool that supports forest inventory in many countries around the world (Dash et al., 2015; Hudak et al., 2008; Næsset, 2004; Stephens et al., 2012). This technology has also been expanded to describe a range of other important vegetation characteristics including biomass (Gobakken et al., 2012), carbon sequestration (Stephens et al., 2012), leaf area index (Tang et al., 2014), and biodiversity (Hill et al., 2005). Tree level studies using ALS, that rely on individual tree analysis (ITA), are feasible and becoming increasingly popular (Dash et al., 2016a). These approaches utilise segmentation and delineation of trees from the ALS point cloud, often based on the CHM raster (Pont et al., 2015), or less frequently from direct interpretation of the point cloud (Shendryk et al., 2016; Zhang et al., 2015). For invasive plant detection, ALS data provide useful structural information that may assist with target plant detection, or in assessing critical aspects of the surrounding vegetation structure.

2.3.2 Imagery collected from piloted aircraft

Imagery collected from piloted aircraft has formed the basis of a significant proportion of remote sensing research, including many studies on the detection and monitoring of invasive species. Studies that use aerial imagery are typically of high spatial resolution and can be differentiated according to the spectral resolution of the sensor deployed. In this review we have differentiated studies into those that use bands within the human visible wavelengths (red, green, and blue), those that use multispectral imagery, that includes a limited number (typically 3 - 15) of bands that include wavelengths beyond those visible to humans, and those that use hyperspectral imagery including more than 15, and often many thousands of bands. The complexity of the sensor is positively correlated with the unit cost and, to some extent, the complexity of data processing and analysis.

2.3.3 Satellite imagery

The advent of data from space-borne Earth observing sensors onboard orbital satellites represented a watershed in remote sensing of vegetation and land-use change. Since the 1972 launch of Landsat-1, the first civilian satellite tasked with observing the Earth, researchers have sought to develop methods to use satellite imagery to enhance our understanding of global systems and vegetation structure. These insights are supported by repeat and detailed data from a range of Earth observing satellites. These are primarily provided by governmental organisations, such as NASA and the European Space Agency (ESA). The great benefit of these platforms lies in the opportunity for a global, or regional, perspective of the Earth's systems. The number of Earth observing satellites, and participating space agencies, has increased dramatically over the past four decades. This is leading to a wealth of data with ever-increasing resolution, return frequency, more sophisticated sensors, and rapidly decreasing data costs (Dash et al., 2016a). Table 2.2 provides a summary of some of the Earth observing satellites that are relevant for invasive conifer detection and may be deployed to provide data for this research.

Table 2.2 Earth observing satellite missions of interest to the detection of invasive conifers in New Zealand. (Sources include (Joyce et al., 2009))

Satellite	Sensor	Spatial Res. (m)	Spectral range	Swath (km)	Bands	Revisit capability
WorldView-2	Multispectral	2.4	410 – 1050 nm	16.4	4	1.1 days
	Panchromatic	0.46	410 – 800 nm	16.4	1	1.1 days
WorldView-3	Multispectral	1.24	400 - 1040 nm	13.1	4	1.1 days
	Panchromatic	0.3	450 -800	13.1	1	1.1 days
Quickbird	Multispectral	2.6	450 – 900 nm	16.5	4	1.5-3 days
	Panchromatic	0.65	450 – 900 nm	16.5	1	1.5-3 days
Ikonos	Multispectral	4	450 – 853 nm	11	4	1.5-3 days
	Panchromatic	0.8	450 – 853 nm	11	1	1.5-3 days
RapidEye	Multispectral	6.5	440 – 850 nm	77	5	1 day
EO-1	ALI	30	4800 – 2350 nm	60	7	16 days
	Hyperion	30	480 – 2350 nm	7.5	220	16 days
Terra	Aster	15,30,90	520 – 1165 nm	60	15	4-16 days
Terra/Aqua	MODIS	250,500,1000	520 – 1165 nm	2300	36	0.5 days
ALOS	PRISM	4	420 - 890 nm	35	4	Several times per year
	AVNIR	10	420 - 890 nm	70	4	Several times per year
	PALSAR(Fine)	10	-	40-70	SAR	Several times per year
	PALSAR(ScanSAR)	100	-	250-350	SAR	Several times per year
SPOT-4	Multispectral	20	650 - 1750 nm	60-80	4	1-4 days
	Panchromatic	10	650 - 1750 nm	60-80	1	1-4 days
SPOT-5	Multispectral	10	480 - 1750 nm	60-80	4	1-4 days
	Panchromatic	5	480 - 1750 nm	60-80	1	1-4 days
Landsat-7	Multispectral	30	450 - 2350 nm	185	7	16 days
	Panchromatic	15	520 - 900 nm	185	1	16 days
Landsat-8	Multispectral	30	450 - 1384 nm	185	8	16 days
	Thermal	100	1060 - 1251 nm	185	2	16 days
	Panchromatic	15	503 - 676 nm	185	1	16 days
Sentinel-2	Multispectral	10	450 - 1384 nm	185	8	8 days

2.3.4 Unpiloted aerial vehicles

In recent times unpiloted aerial vehicles (UAVs) have been shown to be highly valuable tools both for research applications and practical deployments (Dandois and Ellis, 2013; Dash et al., 2017b; Puliti et al., 2017b). Recent improvements in UAV technology, driven by longer flight times and greater carrying capacity, have made them a viable platform for data capture. Sensor hardware manufacturers have recognised this, with several producers developing UAV-specific sensor hardware and numerous start-up companies founded to deliver new options for remote sensing from UAV (Dash et al., 2016a).

Although developing rapidly, the technology that supports UAV operation is still in its infancy. Numerous research teams have published on the development of navigation systems, communications, mission deployment software and sensor integration (Pajares, 2015). Research into UAV systems in the agricultural sciences is well advanced. In this sector UAVs have successfully been deployed for agricultural weed detection (Peña et al., 2013), crop condition assessment, yield monitoring (Shi et al., 2016), and many other uses. Many applications have been developed in the geological sciences, including for landslide monitoring (Al-Rawabdeh et al., 2016). Ecologists have been quick to develop techniques for using UAVs to provide flexible and low cost data to support vegetation assessment (Dandois et al., 2015) and wildlife monitoring (Hodgson et al., 2016). Within the forest sector researchers have made significant progress towards developing UAV systems for tree measurement (Puliti et al., 2017a,b; Wallace et al., 2016b), health monitoring (Dash et al., 2017b), management intervention assessment (Goodbody et al., 2016), and weed monitoring (Watt et al., 2016b). The potential applications of UAV technology are too numerous and broad to list. However, three valuable properties that data collected from UAVs typically bring to invasive plant detection are: 1) ultra-high spatial resolution data that provides an opportunity to push detection thresholds to smaller individual plants, 2) increased flexibility of deployment that means greater opportunity to take advantage of temporary phenological phenomena that may yield improved detection accuracy, and 3) The ability to capture data in cloudy conditions.

2.4 Previous applications of remote sensing for invasive plant detection

Since its first application to forest management in the 1950s (McRoberts et al., 2010) remote sensing has been developed into a powerful tool supporting many aspects of natural resource management. The first instance of the application of remote sensing to detect the presence of invasive exotic plants came from 1993 (Frazier and Moore, 1993) when 46 skilled technicians manually interpreted different size patches of the invasive plant *Lythrum salicaria* using various types of 35 mm file. The results indicated that the accuracy of interpretation benefited from careful selection of the image interpreters. In more recent times we are fortunate enough to have computing capacity that eliminates some of the subjectivity in image analysis.

Huang and Asner (2009) defined a useful method of segregating remote sensing applications for detecting invasive alien plants during an extensive review on the topic. Firstly, they reviewed studies that delineated the presence of invasive species using moderate spatial/spectral and high spatial/spectral resolution remote sensing. Secondly, they described techniques to investigate the phenology (life cycle) of target plants and/or studies that estimate the presence and abundance of invasive plants via high temporal resolution remote sensing. Hyperspectral remote sensing studies were presented to highlight how they can be used to derive the chemical properties of non-native plants. This was followed by consideration of active remote sensing techniques that reveal the vegetation's three-dimensional structure. Subsequently, multi-dimensional analysis that combines the strengths of different types of remotely sensed data via image fusion were presented (Huang and Asner, 2009). In this literature review this approach was followed but extended to include examples where the subject species is not necessarily alien, but is novel in a specific environment, and the subject of detection efforts. A growing, but still small, body of work relies on in-situ sensors to provide near-field, or proximal sensing that can be applied to the detection of invasive plants (Sonnentag et al., 2011). These studies undoubtedly provide a fascinating field of research but, due to the limited spatial extent available from these installations, they are of little value for the focus of this thesis and is not reviewed further.

In total 226 peer-reviewed papers were identified and reviewed based on a comprehensive search of the relevant literature (Figure 2.2). In this literature review the previously reported research into remote sensing for the detection of invasive plants are organised in the following manner:

- Studies based on ALS data.
- Low Spatial/ Moderate Spectral Resolution Remote Sensing = Spatial resolution of >100 m in less than 20 spectral bands.
- Moderate Spatial/ Spectral Resolution Remote Sensing = Spatial resolution of 10 - 100 m in less than 20 spectral bands.
- Moderate Spatial/ Spectral Resolution Remote Sensing with repeat acquisition through time = Spatial resolution of 10 - 100 m in less than 20 spectral bands used.
- High Spatial/ Moderate Spectral Resolution Remote Sensing = Spatial resolution of 0.3 - 10 m in less than 20 spectral bands used.
- Ultra-High Spatial Resolution Remote Sensing = Spatial resolution of <0.3 m, as may be collected from a UAV.

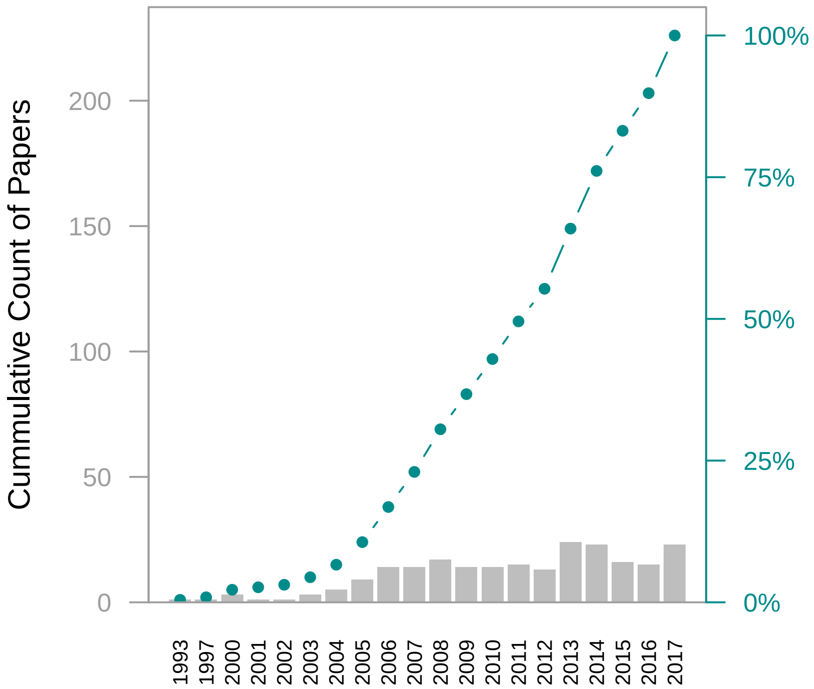

Fig. 2.2 The cumulative sum of peer-reviewed papers detailing research into remote sensing of invasive plants. The grey bars represent the annual count of papers. The turquoise line shows the cumulative sum of papers with the percentage of the total plotted on the secondary y access.

2.4.1 Airborne laser scanning for invasive plant detection

A substantial proportion of the research concerning plant migrations, or invasions, comes from the transition zone between the Arctic tundra and boreal forests. Here, the spread of pioneer conifers are of interest to researchers as it indicates changes in species assemblage that may be associated with climate change. This has been the subject of research particularly focusing on the use of ALS.

Approaches for detecting and measuring trees were developed to monitor the migration of pioneer trees in the Arctic-boreal transition zone through a series of studies dating back to 2009 (Næsset, 2009). In the initial study, the influence of DTM smoothing level and scan acquisition properties on tree detection were investigated. Tree identification was deemed successful if a positive height value was generated from a Lidar echo within the tree canopy, as defined through field work. Using this technique, tree detection was high (91%) for larger (>1 m) trees regardless of the scanner settings or DTM smoothing method used. For smaller trees (<1 m) in the study area only 21 - 61% were accurately detected based on echoes with positive elevation values originating within the tree canopies. Lower pulse repetition frequencies, and greater smoothing during DTM generation, resulted in fewer positive height values and fewer positive detections. The accuracy of tree height derived from the ALS data indicated a systematic underestimation of true tree height by 0.35 to 1.47 m; this was dependent on acquisition settings, terrain model, and tree species. The underestimation was also greater for larger trees. The standard deviation for the differences between laser-derived and field-measured tree heights was 0.16–0.57 m. The significant effects of sensor and flight configurations on tree height estimation mean that field calibration of tree heights at each acquisition of time is required when using airborne lasers for monitoring height development (Næsset, 2009).

In the context of the migration of the treeline at the boundaries of climatic ecotypes researchers are concerned with identifying all trees in the landscape, differentiation of species or tree type is not of concern. To that end ALS is a powerful detection tool as it provides detailed structural information about the target plant. Using the same dataset, and building on the findings of the previous study, an alternative analytical approach was developed that used predictive models based on the ALS data instead of direct detection (Thieme et al., 2011). This resulted in similar results with considerable detection success (90%) for trees taller than 1 m using a generalised linear model. The corresponding classification accuracy for trees shorter than 1 m was 49%. In both studies, the lower detection rate for smaller trees was likely the result of echoes originating in rocks, shrubs, or other features in the landscape (Thieme et al., 2011).

Subsequent studies sought to improve the classification of ALS echoes for identifying pioneer trees using different statistical techniques (Stumberg et al., 2014b). This research compared the performance of the classifiers based on generalised linear models (GLM) and support vector machines (SVM). The inclusion of geo-statistical measures on echo classification was also compared to simpler methods reported previously (Stumberg et al., 2013). The results obtained indicated that including the mean semi-variance derived from the laser height values significantly improved the classification results, but the mean semi-variance based on the intensity values did not.

Due to the large, and inaccessible, nature of the study environment the development of a fully automated unsupervised classification approach for detecting pioneer trees based on ALS data was desirable and was the subject of further research (Stumberg et al., 2014a). The approach developed aggregated areas into homogeneous classes based on statistical parameters that described the point cloud properties. A raster-based algorithm that used a quadtree search approach was developed and, following iterative testing, some guidance was made regarding the initial cell size employed. The results reported indicate that the approach was moderately successful for detecting individual pioneer trees over large areas (Stumberg et al., 2014a).

Tree detection methods that use ALS data are dependent on a high level of vertical accuracy in the point cloud data. This is due to the often limited height of the subject pioneer, or invasive, trees. Vertical height accuracy in ALS data is affected by acquisition settings, such as flying altitude and pulse repetition frequency (PRF) as well as local landforms, vegetation type, and terrain surface in the areas of interest. Previous research studied the effect of these factors on vertical accuracy in the context of detecting pioneer trees in the Arctic-boreal transition zone and found significant differences between different terrain forms and vegetation types. It was also observed that vertical error was minimised at the lowest flying altitude and PRF tested. These findings have significant implications for using ALS to detect small trees in a low biomass environment (Næsset, 2015).

Subsequent research developed a detection and segmentation method based on an allometric model linking tree height to canopy diameter calibrated with local field data. This model was applied to laser echoes with positive elevation values to produce an initial map of possible crown segments. A rule set was then developed to reduce the initial segmentation to a final mean which was validated with field data. This approach achieved fair accuracy with 46% of trees in the study area detected, detection rates were considerably lower for smaller trees, but for trees greater than 3 m detection accuracy was 80% (Hauglin and Næsset, 2016). It is noteworthy that these studies all had the objective of identifying all trees within the study environment. Due to the limited species diversity and climatic constraints, in this environment most individuals were pioneer Norway spruce (*Picea abies*). For invasive conifers detection in New Zealand the problem is significantly more complex as there is generally a significant component of non-target woody vegetation that is not separable from the target trees using structural information alone. Initial methods have been developed to improve differentiation through fusing ALS data with data from other sources. These data fusion studies will be summarised in detail in later sections.

2.4.2 Low Spatial/ Moderate Spectral Resolution Remote Sensing

Low resolution imaging of the Earth's surface is available from several long persisting, and highly valuable, satellite missions. These products provide vital information on global ecosystem functioning and patterns of land use change. Many habitats are more vulnerable to invasion following disturbances, such as wildfire, and management efforts in some environments seek to reduce the spread of invasive species through re-seeding efforts. Following a managed burn in a case study in Idaho, USA, post-fire remediation through re-seeding was trialled to prevent the incursion of invasive shrubs. The response of the burned area following this management activity was monitored using moderate resolution MODIS (spatial resolution = 1 km) data with reasonable success. The authors concluded that MODIS was a useful tool for monitoring the response of a disturbed environment to post-fire reseeding (Chen et al., 2012). In a similar fashion a dense time series of coarse spatial resolution (1 km) MODIS data was used to monitor forest recovery in Louisiana, USA, following damage from Hurricane Katrina (Landfall 25 August 2005). Despite the coarse spatial resolution of the imagery used, the researchers were able to identify areas where canopy recovery lagged due to stand level replacement by invasive tree species (Ramsey et al., 2011).

Degraded agricultural land that results from invasion by exotic species has been identified in previous work using time series MODIS (spatial resolution = 1 km) imagery (Alves Aguiar et al., 2010). A wavelet technique was applied at three different levels of decomposition to remove noise in the MODIS data prior to classification based on vegetation indices using the WEKA J48 classifier (www.cs.waikato.ac.nz/ml/weka). The results of this analysis showed that pastureland could be effectively distinguished from savannah. However, the differentiation of different types of pastureland was poor, suggesting that imagery of this type has insufficient resolution for this task (Alves Aguiar et al., 2010).

Time series MODIS imagery (spatial resolution = 250 m) has been researched as a tool to map the spread and understand the invasion dynamics of buffelgrass (*Pennisetum ciliare*) in Southern Arizona, USA. The results reported from this research showed that buffelgrass abundance increased after significant rainfall and buffelgrass incidence was mapped with moderate accuracy (49 - 55%) using MODIS derived NDVI. This information can be used by land-managers to inform control activities (Wallace et al., 2016a).

2.4.3 Moderate Spatial/ Spectral Resolution Remote Sensing

The definition of moderate spatial/spectral resolution remote sensing involves data collection at a ground sampling distance (GSD) of 10-100 m in less than 20 spectral bands (Huang and Asner, 2009). Studies of this type include those using the European Space Agency's Sentinel-2 imagery Landsat Thematic Mapper (TM)/Enhanced Thematic Mapper Plus (ETM+), Satellite Pour l'Observation de la Terre (SPOT) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER).

Landsat ETM+ imagery (spatial resolution = 30 m) was used in combination with field data and landscape pattern metrics to model native and invasive exotic plant species richness in an oak savannah landscape in Ohio, USA (Schetter et al., 2013). This dataset was used to explain the land cover composition and species richness in the study area with models able to account for between 37–77% of the variation.

The same image source (Landsat ETM+) has been used to monitor the invasive shrub *Rosa rubiginosa* in Southern Patagonia. The locations of the shrub were recorded in the field using a handheld GPS device and used to build a maximum entropy (MaxEnt) model. A range of vegetation indices derived from the Landsat imagery were used, alongside topographic variables, as explanatory variables in the MaxEnt. The model developed showed significant accuracy levels for predicting the location of the target species in a range of environments within the study area. Furthermore, the model could be used to identify areas at high risk of invasion. This served as highly useful spatial data for managers, helping to inform management practices (Zimmermann et al., 2011).

Identifying landcover classes following disturbance (e.g. through fire, abandoned agriculture) and subsequently invaded by exotic plants, including bracken fern *Pteridium aquilinum (L.) Kuhn*, is of significant interest to researchers in tropical regions. In Mexico's Yucatan peninsula land-cover transformation was monitored using Landsat ETM+ imagery analysed using a linear mixture model (LMM). The results of this study showed an increase in the areas affected by bracken fern by 100% between 1989 and 2000. The map accuracy was validated through aerial sketch mapping at the end of the study period (2000) and was found to have achieved a high level of classification accuracy. The authors noted that this remotely sensed imagery enabled an enhanced understanding of the expansion of bracken fern in this context which could lead to better management (Schneider and Fernando, 2010).

Prior to human colonisation the Galapagos islands were dominated by native grassland vegetation, while in recent times the invasive tree *Psidium guajava* has become locally dominant across significant areas, threatening the island's unique biodiversity. SPOT-4 imagery (spatial resolution = 30 m) was used to derive a raster detailing the distribution of NDVI over the island. This raster was subsequently used in a supervised classification based on the simplistic minimum distance method. The *Psidium guajava* affected areas in the study area could be accurately mapped in this manner and this output was used for further modelling of its distribution and predicted spread throughout the islands.

Several studies have compared the efficacy of moderate resolution imagery with high-resolution imagery for detecting invasive plants. A multi-scale approach to monitoring the assemblage of sage brush plants in the sage brush ecosystems of Wyoming, USA, that is threatened by the incursion of invasive plants. A range of different remotely sensed data including Quickbird (spatial resolution = 2.4 m), Landsat ETM+ (spatial resolution = 30 m), and Advanced Wide Field Sensor (AWiFS) (spatial resolution =

56 m) imagery were used in combination with regression trees to identify the structure and composition of the plant community present. The classification performance was inversely correlated to the resolution of the imagery, although all three data types tested outperformed the traditional field-based approach used for monitoring the environment in the study area (Homer et al., 2012). The study also compared the relative costs and accessibility of the data sources tested and identified a cost-effective method for update based on targeting the higher resolution data to areas where significant change has been detected using the lower resolution imagery.

In another comparison of imagery with different resolutions, twenty vegetation indices (VI) were derived from Landsat and Ikonos (spatial resolution = 3.2 m) imagery. The predictive capability of these VIs was investigated for classifying areas infested with the invasive shrub Lantana (*Lantana camara L.*) from other land uses in the Himalayan region of Northern India. Lantana infested areas were found to be spectrally distinct from other land-use types. Of the VIs tested, the soil adjusted vegetation index (SAVI) was the most useful for differentiation followed by the perpendicular vegetation index (PVI) (Kandwal et al., 2009).

A further study of satellite imagery with differing resolutions used a combination of Landsat 7, Ikonos and SPOT imagery to map the invasive giant reed (*Arundo donax L.*) from the common reed (*Phragmites australis (Cav.) Trin. ex Steud*) in riparian areas of Western Portugal. In this environment the giant reeds are invasive and reduce biodiversity amongst assemblages of native plants. A field survey was used to collect spectral data by using a field spectrometer (ASD FieldSpec3) and a bucket truck for access. Samples were collected from areas of giant reed in various phenological periods and from other representative vegetation types in the area. Following dimensional reduction, classification and regression trees (CART) were used to further reduce dimensionality and discriminate the giant reed from adjacent vegetation. A novel statistical approach based on Jeffries Matusita and Bhattacharya distance was then used to evaluate the spectral separability using the minimum optimal bands and in three satellite images from Landsat 7, Ikonos, and SPOT. The results indicated that the subject plant was separable from adjacent vegetation during all phenological stages tested. The red edge region was repeatedly selected as the most important spectral band although the visible region was also important to separate the giant reed from adjacent vegetation. An interesting finding of this research was that Landsat was the most suitable for spectral discrimination due to the higher number of spectral bands (6) than either Ikonos or SPOT imagery (Fernandes et al., 2013).

Brassica tournefortii (Sahara mustard) is native to North Africa but has become a highly invasive plant in desert ecosystems in the USA, and other parts of the world, where it can form thick clumps and monopolise all available water. Sankey et al. (2014) compared the utility of WorldView-2 (spatial resolution = 2.4 m) and Landsat ETM+ (spatial resolution = 30 m) for detecting Sahara mustard. Using mixture tuned match filtering (MTMF) for image classification the authors found that the WorldView-2 imagery provided a much greater overall accuracy than the Landsat ETM+ (Sankey et al., 2014).

The distribution of the central American Mimosoid tree species *Leucaena leucocephala* has been mapped in the tropical coastal region of Taiwan using a combination of SPOT and Formosat-2 satellite imagery. A spatially explicit logistic regression embedded cellular automaton (CA)-based species expansion model was developed using the satellite imagery. The study results showed that the enhanced CA model precisely (95% overall accuracy) predicted the population expansion of the target plant (Lu et al., 2013).

2.4.4 Moderate Spatial/ Spectral and High Temporal Resolution Remote Sensing

The capacity for regular return imaging over an area of interest is a significant strength of satellite imagery. Incorporating time series imagery adds an additional dimension to remotely sensed data that can have considerable advantages in detecting invasive plants. This is particularly true for target plants that display some attribute that makes them separable from their surrounding vegetation during certain periods of the year. Phenological detection approaches make use of this phenomenon by detecting periodic changes, such as flowering or leaf extension to detect the presence of a target plant. Changes in land-use or species assemblage can also be monitored through time in this manner, providing considerable insight into the spread of invasive plants. In this section we review the studies that utilise imagery with a moderate spatial and spectral resolution, and make use of periodic image acquisition. All but one of the studies summarised in this section used the Landsat archive. This emphasises the value of this resource for ecological monitoring at global and regional scales and over extended periods.

In coastal Portugal, a 15-year time series of Landsat TM / ETM+ NDVI images was used to monitor vegetation trends (de Sa et al., 2017). These trends were subsequently integrated with information about disturbance and management practices to map the current distribution of the invasive tree *Acacia longifolia* with a strong overall classification accuracy (kappa = 0.753). The authors were able to use this time series dataset to comment on the invasion susceptibility of several different land use classes in the study area.

Time series imagery provide a unique insight into the recovery dynamics, and ecological succession, of degraded or disturbed lands. These areas are often highly susceptible to invasion by invasive exotic species and monitoring post-disturbance changes in vegetation structure. This was the subject of a study into the open-cast surface coal mines of the Appalachian Mountains, USA (Oliphant et al., 2017). In this research time series Landsat 8 imagery (spatial resolution = 30 m) was used to monitor invasion of disturbed sites by *Elaeagnus umbellata* (autumn olive) which inhibits site recovery by preventing the re-establishment of the native woody plant communities. Autumn olive infested sites were classified with a high degree of accuracy (overall accuracy = 96.8%) indicating that Landsat was a very useful tool for monitoring the invasion of recovering coal mining sites in this environment. Furthermore, the use of time series imagery enabled the authors to identify that mines disturbed prior to 2003, when autumn olive planting was abandoned in the area, contained significantly more of the invasive species than those disturbed more recently (Oliphant et al., 2017).

Also using Landsat TM (spatial resolution = 30 m) data West et al. (2016) present an approach to identifying tamarisk (*Tamarix spp.*) which is a European native tree that is invasive in riparian areas in the USA. This study was focused on the Arkansas River in South-eastern Colorado and described analysis in the software package Software for Assisted Habitat Modelling (SAHM). Within SAHM the authors compared the performance of several ensemble classification approaches to identify tamarisk using vegetation indices (NDVI, SAVI, and tasseled capped transformations) calculated from the Landsat TM imagery. The image classification approaches were combined with a species distribution and achieved accurate results for mapping the invasive species in the riparian zones around the Arkansas river based on a validation using an extensive field sample plot dataset.

Multi-seasonal time series Landsat TM imagery has been used to map the invasive shrub saltcedar (*Tamarix ramosissima*) in the Western USA and northern Mexico. Validation of the distribution model by ground survey (n=79) indicated that the time series imagery could be used for species monitoring and that VIs such as NDVI could be successfully used to clearly identify and map areas infested with saltcedar in this environment (Sridhar et al., 2010).

A study in the coastal waters of Xiangshan Bay, China, found that time series Landsat TM imagery from 2003, 2009 and 2014 could be used to monitor the spread of the invasive aquatic plant *Spartina alterniflora* (Zhu et al., 2016). In this research the distribution of the plant in the study area was characterised and used to draw inference about the life history traits of the species and the anthropogenic influence on its spread in the study area.

The exotic plant *Spartina alterniflora* was introduced to Yuequing Bay in China to assist with land reclamation and to provide defence against typhoon flooding and damage in urban areas. *S. alterniflora* has since become invasive in this environment and has spread extensively throughout the study area. Wang et al. (2015) mapped *S. alterniflora* using a time series of Landsat imagery (spatial resolution = 30 m) and SVM between 1993 to 2009 and SPOT6 (spatial resolution = 6 m, multispectral) imagery with OBIA in 2014. In situ measurements and UAV data were used for validation and to provide supplementary data. Both methods enabled mapping the spread of *S. alterniflora* throughout the study area with a high degree of accuracy allowing the authors to comment on the ecological and environmental implications (Wang et al., 2015).

Dry season imagery from the Landsat archive between 1984 and 2009 has been used to detect the spread of the introduced mesquite (*Prosopis spp.*) tree species in arid and semi-arid areas of Sudan (Majdaldin et al., 2016). This analysis was based on indices including soil adjusted vegetation index (SAVI) and NDVI. Through this analysis the authors were able to monitor changes in vegetative areas for both the indigenous and the invasive species in the region and it was found that NDVI was highly useful for this purpose.

Publicly available remote sensing data products including the Landsat archive and aerial imagery collected by the National Agriculture Imagery Program (NAIP) were the subject of research designed to enable mapping of invasive *Phragmites* grasses in the Detroit river (Xie et al., 2015). The techniques developed in this research enabled the integration of high and moderate resolution imagery and the integration of field reference data with interpreted and classified images in an analytical framework. This allowed the monitoring of an invasive plant with a significant detrimental impact using freely available imagery.

Time series imagery from the Landsat archive was used to develop methods for monitoring land-use change in southern Californian shrubland following short-interval fires (Meng et al., 2014). The study authors hypothesised that the short-interval fires could facilitate the spread of exotic annual shrubs and results in land use type conversion. Linear regression was used to investigate whether there was evidence for type-change in once, and twice, burned areas using the normalised burn ratio (NBR) calculated from Landsat imagery. The study results found some evidence for a reduced vegetation cover at lower elevations but no evidence for a type-conversion from shrubland in the study area associated with periodic fires (Meng et al., 2014).

Multi-temporal remote sensing data from the Landsat ETM+ archive has been used to track vegetation changes in the Big Sage Brush ecological sites in northern Utah, USA (Hernandez and Ramsey, 2013). Soil adjusted vegetation index (SAVI) was calculated from the time series imagery between 1984 and 2008 and used, alongside topographical and climatic variables, to monitor ecological change including that caused by the presence of invasive shrubs.

In the Himalayan foothills of the Indian sub-continent the branching pseudocereal *Hyptis suaveolens* (L.) (pignut) is an emerging invasive plant introduced from tropical America. Detecting and monitoring the spread of this plant in this environment is of significant interest to land managers in the region. In this context, research has been developed to attempt to develop satellite imagery data as a tool for this purpose (Padalia et al., 2013). Remotely sensed data for this study came from the advanced land imager (ALI) onboard NASA's Earth Observation 1 (EO-1) satellite. The ALI imager provides data with a spatial resolution of 30 m in nine spectral bands (0.433 - 23.50µm). Time series ALI imagery was used for sub-pixel classification analysis to identify the target plant in the study area. Classification was based on visual interpretation of the imagery and delineation of severely infested sites; these were verified through field checks. The study results showed that accounting for the phenology of the target species when using ALI imagery and a sub-pixel approach and the time series aspect was critical for successful classification. The authors suggested that the results applied could be improved by extending the approach to take advantage of the hyperspectral Hyperion satellite.

Multi-temporal stacks of imagery from long lived sensors, such as Landsat, can be extremely powerful for mapping the invasion of sensitive environments by invasive plants. Singh and Glenn (2009) even suggest that incorporating spectral bands from multi-temporal imagery can effectively increase the spectral resolution of imagery in a mathematical context. Multi-temporal spectral unmixing was used to delineate cheatgrass (*Bromus tectorum*) from soil and surrounding vegetation with 77% accuracy. The authors note that the phenological differences of this species with the surrounding vegetation make it an ideal candidate for spectral differentiation of this type.

Detecting invasive plants in the forest understorey is particularly challenging for approaches based on passive remote sensing data. Multi-temporal datasets provide a possible solution, particularly when the subject plant is phenologically distinct from the overstorey species. Amur honeysuckle (*Lonicera maackii*) in deciduous forests in the mid-western USA provides a suitable study system to test this. The target plant exhibits leaf expansion earlier than the overstorey vegetation resulting in a distinct temporal signature that can be identified remotely. Using image differencing from time series Landsat ETM+ data Amur honeysuckle was detected with considerable accuracy within a study forest and NDVI was found to be the most instructive VI investigated. A predictive model fitted, based on a quadratic linear function, was found to provide a practical solution for mapping the presence of the target understorey plant (Wilfong et al., 2009).

Time series imagery from Landsat TM was used for monitoring the spread of invasive reed species in wetlands in South Kansas, USA over a fifteen-year period. The results suggest that multi-temporal remote sensing methods are well suited to capturing qualitative information on change in wetlands and other similar environments observing fuzzy and often shifting transitions between land and water (Pavri and Aber, 2004). Also using a Landsat TM time series previous research has monitored the spread of the invasive plant cheatgrass *Bromus tectorium* through the north central Great basin, USA, between 1973 and 2001. Over this period cheatgrass extension was linked to the proximity of various land uses including cultivation, roads, and power lines (Bradley and Mustard, 2006).

Time series aerial imagery has been used to monitor land-use change in relation to invasion by woody plants across a heterogeneous landscape in the North Eastern United States. This research found that land use patterns had a major influence on the abundance of invasive species with deserted agricultural use resulting in a greater abundance (Mosher et al., 2009).

2.4.5 High Spatial/ Spectral Resolution Remote Sensing

High spatial and / or spectral resolution remotely sensed datasets represent a significant portion of the previous research on detecting invasive plants. These studies encompass a wide variety of environments and include the use of airborne hyperspectral data and modern large commercial optical satellites. As this section is lengthy, the studies have been further divided into those using satellite platforms and those using conventional piloted aircraft

Satellite platforms

A multi-scale approach using bi-seasonal Pleiades 1A (spatial resolution = 0.5 m, four spectral bands), RapidEye (spatial resolution = 5 m, five spectral bands), and Landsat-8-OLI (spatial resolution = 30 m, four spectral bands) was used in a study in the Western Himalayas region of India. The study objective was to monitor the spread of *Lantana camara L.* a common invasive species, associated with a significant decrease in biodiversity in infested forests, within the deciduous forests of the study area (Khare et al., 2017). The two-stage analytical approach followed in this study used field data and OBIA with very high-resolution Pleiades data in the first stage to find areas infested with *Lantana camara L.*. This was then used to quantify the diversity of the forest in these regions by extending the remote sensing techniques proposed by Rocchini et al. (2010, 2013) and build models linking these metrics to the lower resolution data. In the second stage a multi-resolution approach, purely based on remotely sensed data, was used to attempt to map the subject species across the entire region. The authors concluded that the results of this study clearly indicated that, as the spatial resolution increases, the approximation of invasive plant species diversity improves. Furthermore, detailed information derived from OBIA classification of very high spatial resolution Pleiades 1A could be applied for the identification of small, newly established populations of invasive plants which, if removed, could effectively limit their further dispersal (Khare et al., 2017).

Building on earlier research with Sentinel-2 data (Ng et al., 2016, 2017) used satellite imagery products with variable resolutions to map the distribution of the invasive woody tree *Prosopis* that was introduced into the Baringo region of Kenya to provide a source of firewood and to prevent desertification. In this environment *Prosopis* is invasive amongst native species and is threatening the abundance of the native tree *Vachellia tortilis* that has significant biodiversity value. The study used imagery from Sentinel-2 (spatial resolution = 10 m) and Pleiades (spatial resolution = 2 m) to develop an object-based random forest classifier. Based on independent validation and out-of-bag (OOB) errors, the study results indicated greater accuracy with the higher resolution imagery. However, the free-of-charge Sentinel-2 data provided a viable alternative for differentiating and mapping the distribution of both *Prosopis* and *Vachellia tortilis* in this ecosystem (Ng et al., 2017).

In an arid environment in Tamil Nadu state in South India, previous research has used imagery from the Indian Space Research Organisation's (IRSO) Resourcesat-2 (spatial resolution = 5.8 m, three spectral bands (green, red, near-infrared)) to map the invasive shrub *Prosopis juliflora* (mesquite) (Vidhya et al., 2017). The subject plant was easily identifiable in the imagery as it glowed significantly in the near-infrared when compared to the surrounding native vegetation. Rasters detailing NDVI were calculated across the study area and a SVM with a polynomial kernel was used for classification. This resulted in an exceptional classification accuracy (kappa = 0.92) indicating that differentiating the subject species in the study environment was straightforward using NDVI. The authors suggest that the utility of NDVI for distinguishing *Prosopis juliflora* from the surrounding vegetation was related to biophysical parameters in the environment (Vidhya et al., 2017).

Mesquite is the common name for a genus *Prosopis spp.* of leguminous small-trees and shrubs native to the South-western USA that is invasive in dry areas of Western

Australia. A recent study used a single image from Digital Globes WorldView-2 (WV2) satellite (spatial resolution = 2 m, 7 spectral bands) to develop methods for distinguishing mesquite in a 430 ha area of the arid Forescue River delta, north-west Pilbara, Australia. Detection was complicated because a significant proportion of the trees were defoliated in the imagery, but the authors were able to achieve good detection accuracy (overall kappa = 0.71–0.77) using OBIA and discrimination analysis. Accuracy rates were increased by limiting the spectral bands used to those informed by a preliminary analysis and the authors noted that even with the best performing detection model omissions were unacceptably high for smaller objects ($<$16 m^2). The results of this study indicate that the new generation of high spatial, and spectral, resolution satellites such as WorldView-2, that have high data acquisition costs, have significant utility for identifying invasive plants.

In the vicinity of Walpole Island, Canada, a single WorldView-2 (spatial resolution = 0.5 m) image has been used to map the density of *Phragmites australis* in environmentally valuable wetland areas (Lantz and Wang, 2013). In this study, OBIA and per pixel maximum likelihood classification were used on 4-band (mimicking imagery from the WorldView-1 satellite) and 8-band imagery. Higher classification accuracy was achieved when using the eight-band image compared to the 4-band image. However, regardless of the bands used the OBIA approach resulted in greater accuracy than the pixel-based classification approach in this instance. The authors concluded that WorldView-2 satellite may be an option for mapping *Phragmites australis* for management, as a single date image can provide high accuracy for the invasive wetland plant (Lantz and Wang, 2013).

In recent years, the China Centre for Resources Satellite Data and Application (CRSDA) has rapidly developed advanced Earth observation capability through the launch of a series of orbital satellites. The ZiYuan1 (ZY-1 02C) and ZiYuan3 (ZY-3) satellites, launched in 2011 and 2012, are amongst this array of space-borne sensor capability. The ZY-1 02C satellite offers both panchromatic (spatial resolution = 5 m) and multispectral (spatial resolution = 10 m) imagery and ZY-3 provides multispectral imagery (spatial resolution = 5.8 m) only with spectral bands that are complimentary and allow the satellites to work in tandem to provide a powerful multispectral dataset (spectral bands = blue, green, red, near-infrared) for land use classification and vegetation assessment. A study in the Jiuduansha Wetland, in the mouth of China's Yangtze river (Lin et al., 2015) developed an approach based on imagery from ZY-1 02C and ZY-3 to monitor dominant plant species including the spread of the invasive cordgrass Spartina alterniflora. One hundred and fifty-six 10 m square sample points were used to identify spectral differences between the vegetation types present and train a classifier based on NDVI. A decision tree classifier was developed in ENVI software and used to identify the four dominant plant species in the area. The results provided an overall classification accuracy for plant species of 87.17% (kappa = 0.81). This suggests that the classification method could effectively identify the dominant plant species in the study area. The results obtained were used to infer the ecological dynamics of the dominant plant species in the study area. The proliferation ability and competitive advantage of Spartina alterniflora limited the expansion of the native plants and control methods are required (Lin et al., 2015).

The mangrove *Sonneratia apetala* was introduced to the Dongzhai Harbour region of Hainan Island, China, from Bangladesh, in 1985 to protect the coastline from storm damage and to replenish the declining native mangrove forests in the area. Since its introduction there have been concerns that the planted species may become invasive and out-compete the native mangrove populations in some environments. The distribution of *Sonneratia apetala* in Dongzhai harbour was investigated using imagery from QuickBird (spatial resolution = 0.6 m) and Ikonos (spatial resolution = 1 m) and validated the results of this analysis using field data (Xin et al., 2013). The results of this mapping exercise were then used to analyse the community structure of the mangrove forests in the study region. As a result, it was observed that the native mangrove species were frequently found in the *Sonneratia apetala* plantations and that, in these environments, native mangrove seedlings were abundant. This indicated that the species were not invasive in the area and that *Sonneratia apetala* could be safely used as a pioneer species to assist with recovery of the native mangrove forests in Dongzhai harbour (Xin et al., 2013).

The spectral angle mapper (SAM) classification algorithm can be used to identify target species through calculating the angle in spectral space between a target set of pixels and a set of reference spectra (end members). The SAM classification approach has been widely implemented for invasive plant detection in many environments (Burai et al., 2011; Lass et al., 2005; Narumalani et al., 2006). The approach allows for image classification based on spectral similarity. Nguyen et al. (2011) used SAM in combination with field spectroscopy and imagery from the Hyperion sensor onboard EO-1 (spatial resolution = 30 m, 220 spectral bands) to map the distribution of the invasive plant pepperweed (*Lepidium latifolium*) in the marshlands of the southern San Francisco Bay, USA. Classification accuracy was 71% and the resultant maps were used to model pepperweed susceptibility in the area using a GAM (Nguyen et al., 2011). The SAM technique was also used for classification based on MNF dataset extracted from hyperspectral imagery for monitoring the plants goldenrod (*Solidago spp*) and milkweed (*Asclepias spp.*) in the Mid-Ipoly-Valley near the Hungarian-Slovak border. Prior feature selection was used before classification to improve the classification performance (Burai et al., 2011). The SAM technique has also been applied to the mapping of willow (*Salix spp.*) in riparian areas with some success (Noonan and Chafer, 2007).

Hyperion time series imagery can be a particularly valuable resource for acquiring cloud free mosaics, this is especially beneficial in tropical areas where cloud free days are limited. Time series moderate spatial resolution (30 m) hyperspectral data from the Hyperion sensor spanning several years have been used for monitoring the highly invasive trees (*Psidium cattleianum*) and (*Morella faya*) in tropical Hawaiian forests (Somers and Asner, 2012). Quantitative evaluation using the separability index found that native trees in the study area were separable from the invasive tree based on their near-infrared reflectance. Phenology was key to successful separation in this study with the authors noting that the spectral difference in the near-infrared was more pronounced in summer than during other seasons. These results provided the basis for operational invasive species monitoring using space-borne hyperspectral imaging (Somers and Asner, 2012).

Identifying individuals present in the forest understorey represents a significant and complex challenge for detection of invasive plants. Shouse et al. (2013) compared the efficacy of high spatial resolution (0.3 m) aerial imagery and moderate resolution satellite imagery (Landsat TM) for identifying bush honeysuckle (*Lonicera maackii*) in the understorey of urban forests in Cherokee Park, Louisville USA. This study was carried out in leaf-off conditions in the deciduous forests of the area and compared a pixel-based approach method (NDVI differencing) with OBIA for both image types. Both analytical techniques yielded accurate classification of bush honeysuckle using the high-resolution aerial imagery, although OBIA performed better than the pixel-based approach. By comparison, the medium resolution Landsat 5 images were only moderately useful for mapping bush honeysuckle in the study area. The coarser spatial resolution Landsat imagery was not useful for identifying individual honeysuckle bushes and resulted in a large omission rate (47.8%). Also working with an invasive understorey plant Niphadkar et al. (2017) compared pixel-based and object-based approaches to detect the invasive plant *Lantana camara* in a tropical forest in Western Ghat, India. high-resolution satellite imagery from Geoeye (spatial resolution = 2 m, spectral bands = 4) and WorldView-2 (spatial resolution = 2 m, spectral bands = 8) were used to identify the small-leaved shrub that grows in thickets in the forest understorey with reasonable accuracy. The high spatial resolution of the satellite data was identified as an important factor in this result.

Imagery from the QuickBird satellite (spatial resolution = 0.61 m, 4 spectral bands) was used, combined with biophysical parameters derived from a DTM, to detect the small, invasive, tree *Miconia calvescens* in the tropical rainforests of French Polynesia (Pouteau et al., 2011). Following pre-processing, the authors compared the classification accuracy of Genetic Algorithm for Rule-set Production (GARP) and SVM to identify areas invaded with the target species. The SVM approach was found to significantly outperform GARP in terms of classification accuracy in this case. Interestingly the biophysical descriptors extracted from the DTM were sufficient to map the distribution of the target tree in this environment. This finding was interpreted as indicating that the potentially invadable area, within the appropriate ecological niche, is saturated in the study area (Pouteau et al., 2011).

The spread of several invasive wetland reed species (*Trapa natans, Phragmites australis, and Lythrum salicaria*) in the 697 ha Tivoli Bays tidal wetland in Dutchess County, New York, was mapped using spectral and textural metrics derived from a single Ikonos image (spatial resolution = 3.2 m). Several classification techniques were used and the classification accuracy ranged from 45% to 77%. Maximum likelihood classification relying on the four spectral and 5-by-5 filter textural bands had the lowest overall accuracy. Object-based classification using four spectral bands and 3-by-3 filter textural bands provided the highest classification accuracy in this research (Laba et al., 2010). Ikonos imagery has also be been used to monitor the invasive woody plant

Pittosporum undulatum in a nature reserve that represents the remnant natural forests in the Azores. Segmentation and classification approaches were examined and a strong degree of separation between the main cover types in the area of interest was achieved. Both SVM and maximum likelihood supervised classifiers were used and both showed good agreement with field data. This indicated that the Ikonos imagery, and analysis approach developed, provide an accurate and cost-effective method of mapping the plants in this environment (Gil et al., 2013).

Piloted aircraft

Dronova et al. (2017) used spectral and textural metrics calculated from very high-resolution aerial imagery (spatial resolution = 0.15 m, R,G,B,NIR) to map the invasive grass medusahead (*Elymus caput-medusae*) in a Californian grassland. The authors compared several unsupervised, supervised, and hierarchical object-based approaches to image analysis and found the best results using supervised single-run support vector machine. Textural metrics have also been used for detecting the invasive tree *Leucanena leucocephala* in Taiwan using high spatial resolution QuickBird imagery (Tsai and Chou, 2006; Tsai et al., 2005a).

A study in the Great Salt Lake of Utah, USA, used a species distribution model (SDM) and high-resolution (spatial resolution = 1 m) aerial imagery to monitor the distribution of an invasive wetland plant *Phragmites australis*. Aerial imagery was collected using a piloted aircraft, covered 1874.5 km^2, and included three spectral bands (green, red and near-infrared). Image analysis employed a pixel-based approach and the Random Forest (RF) algorithm. The study results indicated that the area of wetland affected by the invasive could be accurately estimated. It was observed that invasion was worse in areas close to point sources of pollution and through the study findings areas with a high degree of susceptibility to invasion could be identified and used to guide management interventions (Long et al., 2017).

Skowronek et al. (2017b) used airborne hyperspectral data (spatial resolution = 1.8 m, 285 spectral bands) in combination with a field plot sample and a MaxEnt model to map the distribution of an invasive bryophyte *Campylopus introflexus* on the island of Sylt in Northern Germany. Vegetation on the island is dominated by sand dunes and grasslands and in this environment *Campylopus introflexus* could be mapped from this data with an overall accuracy of 75%. By deploying remote sensing data in the manner used in this study the number of field plots could be reduced from 57 to 12 before a significant deterioration in model performance was observed. Following this research the authors concluded that remotely sensed hyperspectral data is a viable tool for mapping invasive bryophytes in sand dune ecosystems providing an alternative to traditional field survey (Skowronek et al., 2017b).

Previous research has examined the performance of several one-class classifiers (MaxEnt, biased SVM, and gradient boosting machines) to identify the invasive grass *Phalaris aquatica* and herb *Centaurea solstitialis* in a pre-flowering state in the Jasper Ridge Biological Reserve in California, USA. The study area had a Mediterranean climate and was dominated by grassland containing areas invaded by alien species, including the study subjects, and areas that contained no non-native species. Field measures were provided by 3 m square field plots and remote sensing data was provided by the Carnegie Airborne Observatory (CAO) Visible-to-Shortwave Infrared (VSWIR) imaging spectrometer (spatial resolution = 1 m, continuous spectral range = 400-2500nm). The overall resulting accuracy was between 72-88% and the maximum entropy classifier displayed the best performance. In this study all the patterns of spatial distribution predicted by all tree classifiers were consistent (Skowronek et al., 2017a). There are several other examples of hyperspectral imagery classification using ensemble type classifiers, and the high dimensionality and the inter-correlated nature of this data suggest that it is a logical approach. Recent examples include approaches based on the popular RF algorithm that have been used to detect the shrub *Solanum mauritianum* in plantation forests (Peerbhay et al., 2015), and the herbs leafy spurge (*Euphorbia esula L.*) and spotted knapweed (*Centaurea maculosa Lam.*) in rangeland environments (Lawrence et al., 2006).

Invasive plants are extremely prevalent in urban environments, where they are often imported for food provision, or amenity values in parks and gardens. In urban areas of Surrey, British Columbia, Canada, an airborne hyperspectral sensor (CASI, spatial resolution = 1 m) was used to detect the invasive vines (*Hedera helix*) and (*Rubus armeniacus*). Field data came from discrete, accessible, patches of the subject plants, these were used to extract spectra from the hyperspectral imagery. This spectral information was used to train a detection model for (*Hedera helix*) and (*Rubus armeniacus*) in the city achieving good accuracy (76.4 - 80%). A further innovative component of this study was the use of pre-existing ALS dataset to produce a CHM and analytic hillshade model. This allowed shaded areas (e.g. from buildings or urban trees) to be identified and masked from the hyperspectral analysis, therefore reducing this source of error during image analysis (Chance et al., 2016). An alternative approach to interpreting airborne hyperspectral data (spatial resolution = 1 m) is presented in a study where land invaded by bamboo (*Dendrocalamus sp.*) and slash pine (*Pinus elliottii L.*) in south eastern Brazil (Amaral et al., 2015). The analytical approach relied on Multiple Endmember Spectral Mixture Analysis (MESMA) applied to the hyperspectral imagery. The results of this study showed that the infrared (IR) band was critically important for detecting differences in vegetation classes using this approach with the invasive plants exhibiting significantly different characteristics in the IR band. The results obtained during the two-endmember modelling were fully translated into the three-endmember unmixed images. The sub-pixel invasive species abundance analysis showed that MESMA performs well when unmixing at the pixel scale and for mapping invasive species in the study environment (Amaral et al., 2015).

The considerable expense of airborne hyperspectral sensors has limited their widespread adoption despite their obvious efficacy when species specific differentiation between plants is desirable. To address this issue, a light-weight hyperspectral sensor, that can be deployed on-board a gyrocopter, has been developed by researchers in Spain (Calviño-Cancela et al., 2014). The system developed included a custom airborne pushbroom sensor with 200 spectral bands (380 - 1000 nm range with spectral resolution of 3 nm). A key attribute of the sensor was its small size and light weight (4.5 kg) allowing it to be mounted on ultra-lightweight aircraft that have some operational advantages over more conventional aircraft used for aerial survey. Imagery acquired using the prototype sensor was used in conjunction with ground-truth data that included patches of the invasive plants (*Acacia melanoxylon*, *Oxalispes-caprae*, *Carpobrotus aff. edulis*, and *acinaciformis*). These data were used to build a classifier using the acquired hyperspectral imagery (spatial resolution = 0.5 m). Classification was conducted using a SVM, as these are well suited to data with high dimensionality, and achieved excellent classification accuracy across the study area with user's and producer's accuracy always exceeding 90% even when working with very small patches (down to 0.125 m^2). The authors note that the lower cost of the new system means that data can be collected more regularly and that this fine temporal resolution combined with a fine spatial resolution make the system well suited to monitoring early stage invasive plant outbreaks (Calviño-Cancela et al., 2014).

Disturbances caused by biotic, and abiotic, factors are an important ecological process in many ecosystems, and are a primary facilitator of the spread of invasive species. The effects of large-scale disturbance caused by hurricanes, or tropical storms, on the growth rate of *Phragmites australis* in the wetlands of the southern United States have been explored using manual interpretation of a database of historic aerial imagery (Bhattarai and Cronin, 2014). Combining information on the growth rate of *Phragmites australis* with historical data on the frequency of disturbance causing weather events, the authors found that the expansion of *Phragmites australis* was strongly and positively correlated with the frequency of hurricane force winds over a broad geographic range. The increased rate of storm activity predicted by global climatic models, as a result of anthropogenic climate change, suggests that there will be a strong link between climate change and the spread of invasive species in the future (Bhattarai and Cronin, 2014).

Airborne hyperspectral imagery (spatal resolution = 1.5 m, spectral resolution = 8.9 nm) has been studied as a tool for mapping the early stage invasion of the alien plant *Solidago altissima* (goldenrod) in moist tall grassland. Based on this data a generalised linear model (GLM) was developed to predict the invasive plant's presence in early spring when it is was directly visible from above due to phenological attributes. Accuracy assessment statistics suggested that a good classification accuracy was achieved, and model selection indicated that three minimum noise fraction (MNF) bands provided the best performing model based on Akaiake information criterion (AIC). These results suggest that hyperspectral imagery is a useful tool for detecting the very early stages of invasion by goldenrod in the study area (Ishii and Washitani, 2013).

The noxious weed Musk thistle (*Carduus nutans*) is an aggressive member of the sunflower (*Asteraceae*) family that is native to North Africa and Eurasia (Milbrath and Nechols, 2004). Livestock do not graze Musk thistle and as a result it out-competes grassland forage species and can come to dominate entire fields with substantial economic and ecological implications (Mirik et al., 2013a). Previous research has sought to differentiate, and map, Musk thistle in grazing land in Parmer County, Texas, USA, using aerial hyperspectral imagery (spatial resolution = 1 m, spectral range = 505 to 900 nm spectral resolution = 0.7 nm) collected both before and during the flowering Musk thistle flowering. Training samples were manually extracted from the imagery to facilitate classification based on the differences in the plant's spectral properties compared to other species or bare earth in the study area. Image classification was via SVM, using a radial kernel, in the ENVI software package, and was extended to more than two classes by splitting the classification task into a series of binary class separations. Classification results were validated using a field dataset and indicated good accuracy levels that were significantly better during flowering (accuracy = 91%) than pre-flowering (accuracy = 79%). The study authors note that hyperspectral imagery is available as a practical tool for monitoring the spread of this invasive weed and planning management activities that may provide increased yields from productive grassland (Mirik et al., 2013a).

The SVM classifier has also been used to detect and monitor two intermixed invasive woody shrubs evergreen redberry juniper (*Juniperus pinchotii Sudw.*) and deciduous honey mesquite (*Prosopis glandulosa Torr.*) in the rangelands and grasslands of the southern Great Plains, USA (Mirik et al., 2013b). In this research, a county wide aerial image mosaic (spatial resolution = 1 m) was extracted from the NAIP provided by the Natural Resources Conservation Service Geospatial Data Gateway and used for classification in the ENVI software. The results indicated that the archive aerial imagery was a useful tool for detecting these invasive plants in the economically important landscape. The authors suggested that the high spatial resolution (1 m) was key to accurately identifying and mapping the plants. The SVM also had the ability to separate between the two invasive species that were the subject of the study. The study authors recommended that this methodology and technology should be considered when fine scale maps are needed for research and land management purposes (Mirik et al., 2013b).

Manual photointerpretation of an archive of aerial imagery has been used for mapping the spread of the invasive reed cattail *Typha spp.* in the Laurentian Great Lakes, USA. Paleo-pollen analysis was also integrated to determine rates of typha expansion over longer periods (Lishawa et al., 2013). The same approach was used to detect the invasive reed *Phragmites australis* in North American (Louisiana) wetlands using interpretation of a historic archive of aerial imagery (Howard and Turluck, 2013) underlining the value of historical datasets of this type.

Weeping love grass (*Eragrostis curvula*) has become a well-established invasive plant in many river environments including the Kinu River, Japan, where it is the subject of control efforts. The probability of establishment of weeping love grass on the river bank was the subject of mapping using airborne hyperspectral imagery and logistic regression (Lu et al., 2012). The classification based on minimum noise fraction (MNF) was highly successful for identifying the subject plant (Kappa = 0.74). The MNF transformed hyperspectral bands were found to be significantly more suitable that the original hyperspectral reflectance bands for this task (Lu et al., 2012). The superior performance of MNF over the base spectral bands in hyperspectral imagery is a recurring theme in this research (Burai et al., 2011; Ishii and Washitani, 2013; Lu et al., 2012; Narumalani et al., 2006, 2009; Tsai et al., 2005b; Underwood et al., 2003; Yang and Everitt, 2010).

Brazilian pepper (*Schinus terebinthifolius*) is an invasive tree in southern Texan forests that requires management to prevent disturbance and changes in forest structure and biodiversity. To develop a method for mapping Brazilian pepper in this environment a study was installed using several different types of aerial imagery and used supervised image classification to test the suitability for the different imagery types. The results of the analysis revealed that multispectral imagery with bands that included the near-infrared provided the most accurate mapping supporting the use of this data for identifying the target tree in this environment (Fletcher et al., 2011).

Hyperspectral airborne imagery was collected from a twin-engine 404 Cessna using an imaging unit that was sensitive in the 280 to 1000 nm spectral range (Yang and Everitt, 2010). Following extensive geometric and radiometric calibration, mainly in the ENVI software, and minimum noise fraction transformation the imagery was used for supervised classification of two terrestrial weeds, Ashe juniper (*Juniperus ashei Buchholz*) and Broom snakeweed *Gutierrezia sarothrae* (Pursh.) Britt. and Rusby, and an aquatic weed water hyacinth *Eichhornia crassipes (Mart.) Solms*. The spectral un-mixing technique mixture tuned matched filtering (MTMF) was applied to all three case target species and resulted in good classification accuracy. The accuracy of the results was influenced by seasonality and the vegetation composition of the local detection area (Yang and Everitt, 2010). Similar analytical approaches have been developed also using hyperspectral imagery and MTMF to map the distribution of leafy spurge *Euphorbia esula L.* (Glenn et al., 2005; Mitchell and Glenn, 2009; Parker Williams and Hunt, 2002). The overall results in riparian areas of this analysis from Wyoming, USA, were good at all sites but better in prairie areas (r^2=0.79) than wooded sites (r^2=0.57) (Parker Williams and Hunt, 2002).

Hyperspectral airborne imagery (spatial resolution = 1 m, spectral range = 440 - 880 nm) was also used to map the reed *Phragmites australis* in Michigan, USA, using the SAM algorithm. These data were used to generate landscape-scale patterns that quantified ecosystem attributes and human disturbance which were found to moderately influence the percentage cover of the target invasive species (R^2 = 0.4, n = 40) (Torbick et al., 2010).

Many previous studies, including (Andrew and Ustin, 2008) conclude that environmental context is critical for identifying invasive plants. Andrew and Ustin (2008) used airborne hyperspectral imagery (resolution 3 m) to map the invasive shrub perennial pepperweed *Lepidium latifolium* across an environment with a range of habitat conditions. In the simpler environments investigated, in this case the wettest, there was little diversity, and the species was easily spectrally separable from other vegetation. At the most diverse site the target invasive plant was indistinguishable, both spectrally and phenologically, from several co-occurring species and could not be classified accurately. The evidence from this research suggested that the success of remote sensing analysis declines with site complexity. Site complexity is affected by species composition, structural composition, landscape diversity and spectral variability.

Ustin et al. (2002) noted the advent of new hyperspectral sensors that enabled a change from multi-band aerial imagery to the acquisition of more laboratory-like hyperspectral spectroscopy. The authors recognised the potential of this new sensor technology to detection and monitoring the spread of invasive plants and established two case studies to test its utility with imagery that had a moderate spatial resolution (4 m). The hyperspectral analysis improved with the use of MNF, continuum removal, and band ratio indices for mapping ice plant *Carpobrotus edulis* and jubata grass *Cortaderia jubata* in a coastal Californian study site. Validation against a field dataset showed excellent correspondence with MNF producing the best results (Underwood et al., 2003).

In California's Sacramento-San Joaquin River Delta invasive plants are monitored in addition to fluvial dynamics to plan management and maintenance of the navigable waterway. In particular, the invasive submersed plant Brazilian egeria (*Egeria densa*) and the floating plant water hyacinth (*Eichhornia crassipes*) are monitored and managed through herbicide application. The temporal dynamics of these species were monitored over four years between 2003 and 2007 using airborne hyperspectral imagery. The results of this study showed that multi-year treatment decreased the submerged plant's spread and that the Brazilian egeria itself serves as an ecosystem engineer in this environment. The herbicide treatment controlled the year-on-year spread of water hyacinth resulting in an increase in abundance of native plant species once the invasive plant was controlled. The results of this study showed that an integrated management plan was needed in the environment rather than focusing on individual species (Santos et al., 2009).

2.4.6 Ultra high spatial or spectral resolution remote sensing (UAV)

As discussed in previous sections, the emergence of UAVs has significant implications for invasive plant monitoring. There are several examples of UAV-based invasive plant detection studies within the research literature. All aspects of this important emerging research area have been comprehensively reviewed in Chapter 3.

2.4.7 Data fusion for invasive plant detection

Integrating remotely sensed data of different types can provide insight into the object of interest that contains more information than any of the constituent data sources (Xu et al., 2015). Data fusion approaches like this are typically acquired in one of two ways:

1. Multiple sensors with different properties are deployed on the same platform, the resulting datasets are spatially consistent and coherent and can be easily combined.

2. Multiple datasets are collected in the same area of interest in separate campaigns. These can then be integrated in a separate processing step, producing viable data in this manner may require additional rectification of the disparate data or a conversion process.

The following sections provide a summary of previous research that used fusion of remotely sensed data for invasive plant detection.

High-resolution airborne imaging spectroscopy has been used to study the distribution of the invasive tree *Psidium cattleianum* (strawberry guava) in sub-montane Hawaiian tropical forests (Barbosa et al., 2017). The gross primary productivity (GPP) ratio index was used to monitor the difference in GPP between strawberry guava canopies and those of invaded forest types. ALS data, collected simultaneously from the same aircraft, was used to assess the impact of strawberry guava invasion on the above-ground carbon density within the study forest. This research showed that the GPP ratio provided an innovative, spatially explicit, approach to track and predict the progression of alien plant invasion. In combination with environmental data, such as a soils and elevation, canopy productivity was used to accurately predict the presence of invaders and to spatially quantify their impact on the surrounding vegetation within a landscape framework (Barbosa et al., 2017).

Research centred in mixed tussock grassland and shrubland in the foothills of New Zealand's Southern Alps combined high-resolution aerial imagery (spatial resolution = 0.3 m, four spectral bands) and ALS to detect invasive Douglas fir originating in nearby commercial plantations (Dash et al., 2017a). In this research a RF classification algorithm was trained to detect ALS echoes originating from the invasive conifers. The algorithm was based on a combination of the structural data derived from ALS and the spectral information that was found to be useful for differentiating between the invasive conifers and other shrubs and trees in the study area. Model performance indicated a good accuracy (kappa = 0.83) and was deemed to be a useful detection tool for monitoring the distribution of invasive Douglas fir in this environment. In the same paper a simulation study was also undertaken to test the effect of reduced ALS pulse density, a major determinant of acquisition cost, on the accuracy of the approach. This study found that although reducing pulse density did not affect the accuracy of the classification model, lower pulse densities resulted in a lower probability of invasive plant detection as they more frequently failed to be sampled by the laser scanning campaign (Dash et al., 2017a).

In a recent study in the Norwegian boreal forest researchers developed techniques to discriminate the exotic tree Sitka spruce (*Picea sitchensis*), that was planted as a timber resource but has become invasive in certain conditions (Hauglin and Ørka, 2016). In this research three remotely sensed data sources: time series Landsat imagery (spatial resolution = 30 m), aerial imagery (spatial resolution = 0.25 m) and ALS data were used to develop a method for discriminating between Sitka spruce and stands comprised of indigenous conifers. Although a variety of resolution datasets were used, the classification models were developed on a 250 m^2 circular area basis. Ensemble learning classifiers SVM and RF, and the parametric method logistic regression, were used to develop binary classification in this research. The accuracy of the classification models varied between 53% to 79% with the best performance obtained from combining Landsat imagery with aerial imagery and using logistic regression. This is a logical outcome as ALS data is unlikely to be useful as the structural properties of Sitka spruce stands will probably not vary greatly from those of the indigenous trees. Similarly, the size of the area basis used for model development would likely negate any benefits of the higher resolution data (Hauglin and Ørka, 2016).

In an ambitious study in the tropical forests of Madagascar (Ghulam et al., 2014) integrated high-resolution optical satellite imagery (Hyperion, Geoeye-1, Landsat ETM+, Ikonos-2) with microwave remote sensing (InSAR/PollnSAR) to detect sub-canopy invasive plants (*P. cattleianum* (guava), *A. angustifolium* (Madagascan cardamom), *R. moluccanus, Linn* (Molucca raspberry). This research also made use of field data collected from various land uses within the study area and, after comprehensive processing of the various data sources, used a decision tree based classification approach that could incorporate the numerous sensor and data types. The results showed that the very high spatial resolution of the GeoEye-1 sensor meant that data of this type was able to detect Madagascar cardamom and Molucca raspberry even when they were beneath the canopies of surrounding trees. Based on Ikonos-2 multispectral imagery, decision tree classification yielded results that were similar to manual photo interpretation of the aerial imagery. However, decision trees provided advantages in detecting invasive plants in sub-canopy communities. Pixel-based classification approaches were not able to differentiate guava as it had no spectral or textural differences that could differentiate it from other forest types. Using the decision tree algorithm, the overall classification accuracy for all three plants was 83.1% (kappa coefficient = 0.735). The availability of hyperspectral imagery proved vital for accurate discrimination of the various invasive plants but the InSAR and PolInSAR were important in identifying invasive species.

Ultra-high-resolution aerial imagery (spatial resolution = 2 mm) has been used to map the distribution of Dalmatian toadflax *Linaria dalmatica* in mixed- grassland prairie (Blumenthal et al., 2012). Areas of toadflax were manually delineated from the ultra-high-resolution imagery and this data was then used to fit a geo-statistical model of toadflax abundance based on topographic variables and variables related to grazing pressure and predicted snow deposition rates. Information of this type is highly valuable for understanding the spread of invasive plants and planning their management (Blumenthal et al., 2012). In a similar manner aerial photographs were also used to monitor the spread of the South American shrub *Leucaena leucocephala* in Taiwan.

The study authors noted that the phenology of the plant was critical to its detection. This research allowed the authors to monitor the spread of the plant following forest disturbance and found it to be strongly correlated with soil type (texture and acidity) (Chen et al., 2012).

A combination of hyperspectral imagery, ALS data, and time series satellite imagery was used in the Hawaiian tropical forests to monitor biological invasion and habitat response in response to removal of enemy organisms (Kellner et al., 2011). Using these data the authors observed that removal of an ungulate generalist herbivore from the study area resulted in increased invasion by exotic plants but no change in the abundance of native vegetation. A phenological analysis based on the time series satellite imagery was able to differentiate areas immediately following ungulate removal and the enhanced vegetation index (EVI) proved to be a highly useful for this task. The major invasive plant was the forb *Senecio madagascariensis* that increased cover in ungulate free areas from 0.01% to 14.7% but was absent from control areas. This research provides a good example of how remote sensing can be used to understand not only the ecological understanding of a study system but also to provide insight into the efficacy of management in response to invasive species. Previous research also used a fused hyperspectral and ALS dataset to characterise habitat characteristics, including the presence of the invasive tree *Morella faya*, and linked these habitat characteristics to avian abundance (Boelman et al., 2007).

A combination of satellite imagery from LISS-3, LISS-4, and Cartosat-1 have been used to map the distribution of *Lantana camara L.* in the Indian region of the Himalayas. This study included fusion of the LISS-4 and Cartosat-1 imagery using Brovey fusion and incorporated the calculation of textural metrics (Kimothi and Dasari, 2010).

Airborne multispectral imagery and ALS data have been used in a hierarchical OBIA approach to detect Australian pine (*Casuarina equisetifolia*) in a region, containing mixed land use, of Eastern Florida, USA. Following segmentation of the imagery object level spectra, textures, and 3D information were computed and their capacity to separate the target plant in this environment was tested. The best models achieved moderate classification accuracy using the specific geographic image retrieval (GIR) approach developed (Xie et al., 2008).

Combining multiple satellite imaging products provides advantages that are greater than the individual properties of either product alone, whist still providing the benefits of using an orbital spaceborne platform. This was the subject of previous research in Taiwan where a combination of Hyperion (hyperspectral with moderate spatial resolution = 30 m), and QuickBird (very high spatial resolution imagery) were used to detect *Leucaena leucocephala* (horse tamarind). The approach developed is two phase and relies on an initial phase using the Hyperion image to provide a preliminary result of the species location. In the second phase, the high-resolution imagery is used to improve the accuracy of the discrimination. Field validation indicated a high degree of accuracy (Tsai et al., 2005b).

One of the earliest applications of satellite imagery to detect invasive plants relied on data fusion of Ikonos imagery with airborne hyperspectral data. The hybrid unsupervised approach produced better classification accuracy than other supervised approaches trialled (Bachmann et al., 2001).

2.5 Analytical methodology

Invasive plant detection through remote sensing demands some form of image, or point cloud, analysis. There is a significant, and growing, number of techniques that can be included in an analytical framework for detecting invasive conifers. To assist with method development for this research, a summary of some of the more relevant techniques is provided in the sections below.

2.5.1 Spectral detection

The majority of studies into invasive plant detection rely on spectral detection to differentiate between target plants and the surrounding vegetation and fewer studies used object-based, textural, phenological analysis (Bradley, 2014). Spectral detection approaches rely on the feasibility of differentiation between the target invasive plant and other plants within a scene. A spectral distinction implies that the target invasive species has one or more unique light absorption or reflectance features relative to non-target vegetation (Bradley, 2014). Several studies have characterised the spectral properties of invasive plants through the use of handheld field spectrometers (e.g. (Aneece and Epstein, 2017; Chung et al., 2007; Große-Stoltenberg et al., 2016; Ouyang et al., 2013)). Once characterised, these can then be used in combination with remotely sensed data to identify the target plant in a study area. Approaches of this type are reliant on parity between the characteristics of the proximal and remote sensors used, this is easiest when using hyperspectral imagery which has many hundreds of narrow spectral bands (Bradley, 2014). This is evidenced by the extremely large number of studies using hyperspectral remote sensing for detecting invasive plants (section 2.4.5). However, plentiful research also has shown that sensors that use bands in the visual, and multispectral, wavelengths can be highly successful for detecting invasive plants. Once the spectral properties of a plant are fully characterised the expected response of widely used sensors can be simulated using specialist software products. This can assist with sensor selection and can aid spectral detection.

Phenological detection approaches rely on transitory changes in the target invasive plants that make it separable from surrounding vegetation. These changes include flowering, senescence, and leaf flush and these are frequently more effective than leaf pigmentation for invasive plant detection (Bradley, 2014). There are a large number of studies have used temporary phenological aspects of the target plant to differentiate it from surrounding vegetation (Chung et al., 2006; Padalia et al., 2013; Singh and Glenn, 2009; Somers and Asner, 2012; Wilfong et al., 2009). Phenology can vary on a meso or micro scale and this can impact analytical outcomes. For example, flowering may be delayed in cold, shady sites and latitude gradients can impact phenology at a regional or national scale. The success of phenological detection approaches is dependent on timely deployment of an appropriate sensor as the temporary phenology may not last for an extended period. Regular visit satellite imagery offers a potential solution for this, although this may be limited by the presence of significant atmospheric cloud and the chance of unfavourable lighting conditions during image capture. The widespread availability of UAVs, that are flexible enough to be deployed during phenological expression, also has significant potential to provide useful data for phenological detection and there is an expanding number of studies relating to this data source (section 2.4.6).

Previous research into detection through plant phenology has sought to define the optimal time of the year for detection of a range of target species purple loosestrife (*Lythrum salicaria L.*), common reed (*Phragmites australis Cav.*) and cattail (*Typha L.*) in a wetland environment using airborne hyperspectral data (Laba et al., 2010). Radiometric measurements were taken thoughout the year using a handheld fibre optic spectrometer. In this manner this research was able to identify that the target plants were most distinctly separable from the surrounding vegetation in August in the study area. Combining 3D structural data with spectral data can increase the separability of a target plant in a manner that may not be possible using two dimensional data alone (Blaschke, 2010; Dash et al., 2017a).

2.5.2 Object-based and textural image analysis

Spectral detection techniques are reliant on the recognising the unique spectral properties of a subject pixel within a scene. By contrast, object-based image analysis (OBIA), and textural analysis, make use of patterns amongst groups of pixels (Bradley, 2014). Textural analysis takes advantage of particular patterns and direction of groups of pixels. Development of mathematical techniques, such as the development of grey level correlation matrices (GLCM)(Haralick et al., 1973), that quantitatively describe such patterns have been widely used to segment remotely sensed images (Dronova et al., 2017; Feng et al., 2015; Laba et al., 2010; Watt et al., 2016a). By contrast, OBIA is typically focussed on distinguishing specific objects (individual plants, buildings, etc.) from surrounding pixels (Blaschke, 2010; Bradley, 2014). These approaches can be unsupervised or, more frequently, supervised with the latter approach requiring input from an operator and frequently proving more accurate. However, approaches requiring no human input have obvious appeal. These techniques are based on machine learning (Blaschke, 2010) and are reliant on evaluation of variance in reflectance within a multi-pixel moving window (Bradley, 2014). Larger individuals such as invasive trees have frequently been the subject of these studies (Weisberg et al., 2007).

2.5.3 Classification techniques

Whether using spectral detection of pixel-based analysis some form of image classification is required unless manual interpretation is being used. In the following sections some of the commonly used techniques from previous research are summarised.

2.5.4 Minimum Noise Fraction

Minimum noise fraction (MNF) is a popular and well known transformation for reducing noise when working with hyperspectral imagery (Lee et al., 1990). The MNF transform is a linear transformation which is essentially two cascaded Principal Components Analysis (PCA) transformations. The algorithm transforms a noisy data cube into output channel images with steadily increasing noise levels, which means that the MNF output images contain steadily decreasing image quality (Luo et al., 2016) and is typically applied as a pre-classification step during image processing. The objective of applying MNF to hyperspectral data is to remove redundant data, simplify analysis, and improve the accuracy of image classification outputs. Transformed MNF data have several unique and simple properties: they are band decorrelated, have a zero mean, and have unit noise variance. The covariance matrix of an MNF transformed dataset is a diagonal matrix with elements equal to the MNF eigenvalues. The MNF eigenvalues decrease sequentially by band and have a lower bound of one, due to unit noise variance. Because noise eigenvectors have been directly correlated to signal-to-noise ratios, MNF transforms are generally highly effective at signal component organisation (Mundt et al., 2007).

2.5.5 Mixture tuned matched filtering

Mixture tuned matched filtering (MTMF) is frequently used in combination with MNF for classification of hyperspectral imagery (Noujdina and Ustin, 2008) as an approach for partial unmixing and target end member identification (Mundt et al., 2007). This algorithm has been widely applied to invasive plant detection (Section 2.4.5). The MTMF algorithm consists of two phases, a Matched Filter calculation for abundance estimation and a Mixture Tuning calculation for the identification and rejection of false positives (Mundt et al., 2007). In an optical remote sensing context, Matched Filtering can be described as the process of filtering the input data for good matches to the target spectrum while suppressing the remaining background spectra (Mundt et al., 2007). The segregating power in the MTMF algorithm is in the Mixture Tuning, which calculates a value of infeasibility (or a measure of goodness of match) for each MF classified pixel. The MTMF algorithm as described here implicitly requires zero mean, unit noise variance input data (such as MNF transformed data) for proper Mixture Tuning calculation (Mundt et al., 2007).

2.5.6 Spectral Angle Mapper

The spectral angle mapper (SAM) algorithm is a classification method that permits rapid mapping by calculating the spectral similarity between the image spectrum to reference reflectance spectra. The reference spectra are typically either taken from laboratory or field measurements or extracted directly from the image (Girouard et al., 2004; Yuhas et al., 1992). SAM measures the spectral similarity by calculating the angle between the two spectra, treating them as vectors in n-dimensional space. Small angles indicate high similarity, and large angles indicate low similarity (Girouard et al., 2004). The key appealing features of SAM are that it is unaffected by solar illumination, and that it is a fast and easy method of image segmentation through mapping the spectral similarity of image spectra (Girouard et al., 2004).

2.5.7 Random Forests

The ensemble decision tree classifier Random Forest (RF) uses bootstrap aggregated sampling (bagging) to construct many individual decision trees, from which a final class assignment is determined (Breiman, 2001). RF is now regularly applied to natural resource assessment (Mellor et al., 2013) and has previously been used, in combination with remotely sensed data, to successfully model several variables of interest in many forest types (Dash et al., 2015, 2016b; Watt et al., 2015). Decision trees are constructed using a sample from the available training data, with the remaining assigned as out-of-bag (OOB) samples. At each node, a random subset of predictor variables are tested to partition the observation data into increasingly homogeneous subsets. The node-splitting variable selected from the variable subset is that which resulted in the greatest increase in data purity (variance or Gini) before and after the tree node split (Cutler et al., 2007). This process ends when there are no further gains in purity. Response variables can be continuous, calculated by averaging, or categorical where predictions are derived from a model vote among decision trees. Computational efficiency of the algorithm is enhanced, compared with alternative approaches, as only a sample of variables are used at each node split. This also reduces correlation between trees, improving both predictive power and classification accuracy. The OOB sample data are used to compute accuracies and error rates, averaged over all predictions, and estimate variable importance (Cutler et al., 2007; Mellor et al., 2013). RF provides two methods to estimate the importance of each predictor variable in the model. The mean decrease in accuracy (MDA) importance measure is calculated as the normalised difference between OOB accuracy of the original observations to randomly permuted variables (Cutler et al., 2007; Mellor et al., 2013). An alternative variable importance measure is calculated by summing all of the decreases in Gini impurity at each tree node split, normalised by the number of trees (Antonio Criminisi, 2012; Mellor et al., 2013). RF is a well-regarded machine learning tool that can identify complex and non-linear relationships in fitting datasets and has been shown to offer high classification accuracy (Antonio Criminisi, 2012; Cutler et al., 2007; Dash et al., 2016b).

2.5.8 Support Vector Machines

Support vector machines (SVM) is a pattern recognition method based on statistical learning theory. SVM was first developed for classification (Cortes and Vapnik, 1995) but is now mainly used for classification and regression of small non-linear and high-dimensional samples (Yuan et al., 2017). SVM is based on the VC-dimension of statistical learning theory and the minimum structural risk principle. The model learning accuracy is analysed, and learning is performed without error recognition using limited sample information. The minimum deviation of the hyperplane from the sample points is used to obtain the best universal ability (Friedman et al., 2001). Important parameters include the kernel function, which reflects similarity between data points (i.e., between reflectance values) and the cost loss function (regularization parameter) (Verrelst et al., 2012; Yuan et al., 2017).

Support vector machines (SVM) have been widely used in classification of many forms of remotely sensed data including optical data (Foody and Mathur, 2006; Pouteau et al., 2011), synthetic aperture radar (SAR) data, and multiple source fused datasets (Hill et al., 2005; Waske and Benediktsson, 2007), and hyperspectral imagery (Camps-Valls et al., 2006). Previous research has suggested that SVM classifiers offer increased accuracy compared to other algorithms for numerous types of remotely sensed data (Waske and Benediktsson, 2007).

2.5.9 Artificial Neural Networks

Artificial neural networks (ANN) are based on the gradient machine learning method. ANN are powerful non-parametric non-linear model that uses neural network spreading between layers and replicates human brain receivers and information processing (Friedman et al., 2001). Despite this impressive description and complex analogy an ANN is in fact a two-stage regression or classification model, typically represented by a network diagram. These methods have been applied to a wide number of applications including the classification of remotely sensed data. In practice, fitting ANN is a fine art as they are frequently over parametrised and the optimisation problem is non-convex and prone to instability unless certain guidelines are followed (Friedman et al., 2001). ANN includes an input layer, hidden layer, and output layer, as well as network initialisation parameters (e.g., the number of neurons is determined by the input and expected output to initialise weights between neurons), hidden layer, and output layer calculations. The error values and weights are updated to obtain a set of final weights (Yuan et al., 2017), this is achieved using a two-pass procedure known as back propagation (Friedman et al., 2001). There are many important parameters that must be defined by the user in ANN regression models including the number of neurons. The neuron number is positively correlated with the learning accuracy and negatively correlated with the model's generalisation ability (Yuan et al., 2017).

2.5.10 Detection thresholds

In remote sensing studies the detection threshold refers to the minimum object size that can be identified with a given sensor in a given environment. Weber and Chen (2010) assessed the detection threshold for sub-pixel targets based on multispectral Quickbird imagery. Twenty bright blue tarpaulins of various sizes (0.24 m - 2.4 m) were located throughout the study area under various vegetation conditions. The detection threshold of the unique objects in this imagery were then investigated through a series of supervised presence/absence classifications based on the Quickbird data using maximum likelihood classification based on spectral signatures in IDRISI's MAKESIG module. Classification accuracy was strongly related to target size ($R^2 = 0.94$) and training site vegetation status became increasingly important as target object size decreased. When objects covered more than 25% of the pixel then classification provided good results but objects below 25% of pixel size were not detectable.

2.5.11 Accuracy assessment

Classification performance can be assessed using a variety of statistical metrics, these frequently include user's and producer's accuracy and Cohen's Kappa coefficient

(Cohen, 1960) (kappa). Kappa is a widely used metric for assessing the agreement between two sets of observations that is generally deemed to be robust because it accounts for agreements occurring through chance alone. Several authors propose that the agreement expressed through kappa, which varies between 0 and 1, can be broadly classified as slight (0 - 0.20), fair (0.21 - 0.40), moderate (0.41 - 0.60), and substantial (0.61 - 1) (Dash et al., 2017a; Hauglin and Ørka, 2016). To quantify the difference between classification models confidence intervals for kappa values can also be calculated. Receiver operator characteristic (ROC) curves were also used to examine the accuracy of the classification. ROC curves are graphical representations of the accuracy of binary classifiers. The true positive rate (sensitivity) is plotted on the y-axis and the false positive rate forms the x-axis. The ROC curve is plotted by calculating the cumulative distribution function on both axes with a diagonal reference line plotted to indicate where classification is no better than chance. The area under the curve (AUC) can be calculated from ROC curves and is used to quantify classification quality. AUC values for ROC curves vary between 0.5, classification no better than chance, to 1, indicating a perfect binary classification (Dash et al., 2017a).

When calculating accuracy metrics it is good practice to completely separate the validation sample from the training sample. This if often achieved by using leave one object out cross-validation (LOOOCV). Cross-validation processes like this typically exclude a segmented object out from the training dataset and use the remaining objects to fit a classification model. The resultant predictive model is then used to predict classification values for the excluded object. Using this approach provided a completely independent validation dataset for assessing predictive accuracy.

2.5.12 Conclusions

From this comprehensive literature review it is clear that there is a broad and varied body of research relating to the detection and monitoring of invasive plants using remote sensing. This is testament to the importance of the issue of invasive plants globally. Despite this wealth of research there are clear gaps in the knowledge that will be addressed in this thesis. These include the application of UAVs, the early detection of target plants using ultra high-resolution data, the transferrability of invasive conifer distribution models, and the use of time series satellite imagery to track historical spread and control.

Chapter 3

Taking a closer look at invasive alien plant research. A review of the current state, opportunities, and future directions for UAVs

3.1 Preamble

Emerging UAV technology is clearly an important new data source for invasive plant detection and monitoring. In this chapter I have provided a systematic and highly detailed review of all the UAV-based research in this field. The contents of this chapter have been peer-reviewed and published in Methods in Ecology and Evolution. The text is reproduced here with the permission of the publisher.

Dash, J.P., Watt, M.S., Morgenroth, J., Paul, T.S.H., Hartley, R. (2019) Taking a closer look at invasive alien plant research: A review of the current

state, opportunities, and future directions for UAVs. Methods in Ecology and Evolution doi.org/10.1111/2041-210X.13296

3.2 Abstract

1. The development and proliferation of unpiloted aerial vehicles (UAV) in recent years presents a new data collection opportunity for invasive alien plant (IAP) research. The flexibility and cost-efficiency of these craft offers a valuable solution where high-spatial or high-temporal resolution remotely sensed data is required.

2. In this paper we review all published studies using UAV for remote data collection in IAP research.

3. We have systematically identified the taxonomy and habitat characteristics of the system studied, classified the UAV configuration, analytical methods, and the limitations of each study.

4. We used this synthesis to identify research gaps, suggest directions for future research, and identify opportunities for practical application of the technology.

3.3 Introduction

Translocated plants present due to intentional or accidental introduction as a result of human activity are referred to as alien plants (Richardson and Berlyn, 2002). The globalisation of trade and the ubiquity of human travel and migration has resulted in the large-scale distribution of alien plants across the Earth (Kueffer, 2017; Meyerson and Mooney, 2007). A subset of alien plants reproduce freely in their new environment, outcompete, and replace existing vegetation (Richardson and Berlyn, 2002). These species are of concern as they can invade indigenous vegetation impacting biodiversity and ecosystem services (Simberloff et al., 2013; Vaz et al., 2018b) and are recognised as a major component of human-induced environmental change (Hulme, 2003). Invasive alien plants (IAP) often benefit from a different evolutionary history than the recipient biotic community (Kueffer, 2017; Saul and Jeschke, 2015) and many IAP exhibit traits that are not present in native communities (Richardson and Higgins, 1998) affording them a competitive advantage. Without effective management, IAPs will continue to threaten biodiversity and ecosystem function and must be controlled (Hulme, 2003). Effective management must be supported by appropriate methods for detection and monitoring (Richardson and Rejmanek, 2011). Traditional methods including observer-based surveys are expensive, can be error prone, and are difficult in challenging terrain (Dash et al., 2017a). As a result, new modes of detection and monitoring are required.

Remote sensing has matured to provide practical management tools in many domains. Previous reviews of IAP research using remote sensing have reviewed the properties of the datasets (Huang and Asner, 2009), the analytical methods used (Bradley, 2014), and discussed the future applications of remote sensing of plant invasions (Niphadkar and Nagendra, 2016). Others have summarised research relating to a single species (Thamaga and Dube, 2018) or aspects of a management approach (Juanes, 2018). The evolution of remote sensing based IAP research has also been reviewed and used to suggest directions for future studies, technological developments, and planned remote sensing missions (Vaz et al., 2018a). Techniques that provide data at an appropriate scale will enable the development of myriad applications suitable for IAP research. Uses range from the earliest detection of plant invasions to monitoring historical trends in spread at a global or continental scale.

Unpiloted aerial vehicles (UAV) are recently emergent remote sensing platforms. These robotic craft offer automated movement and navigation and can carry a range of sensors to acquire data with finer spatial and temporal resolution than ever before.

Furthermore, UAVs are now available with limited financial investment (Manfreda et al., 2018) and the technological barrier to entry is lower than traditional platforms Dash et al. (2016a); Heaphy et al. (2017). Their versatility, adaptability, and flexibility compared to more established alternatives mean that they will continue to provide a vital data source for IAP research. UAVs also provide safe access to dangerous, or difficult to reach locations where data collection is required (Manfreda et al., 2018; Rivas-Torres et al., 2018; Watts et al., 2012). Moreover, the capacity for data collection under cloudy conditions, that can preclude data capture from orbital satellites and many piloted aircraft, is a significant advantage. This is particularly important in tropical and maritime areas where successful collection of cloud-free satellite imagery may be as low as 20% of the total overpass rate (van der Wal et al., 2013).

There are many benefits of using UAVs for data acquisition, but several limitations remain that require research effort to overcome. These include constraints in areal coverage as the range that can currently be covered efficiently by UAVs is relatively small. Therefore, UAV data are frequently augmented with data from other platforms to provide insight over larger areas. The immaturity of the UAV domain is also an impediment with legislation, data processing pipelines, and sensor sophistication all lagging the pace of development and demand for UAV data.

The favourable properties of UAV-borne remote sensing systems mean that they have been successfully, and repeatedly, used for data collection (Manfreda et al., 2018; Pajares, 2015) for a wide range of applications (Baena et al., 2018; Dandois and Ellis, 2013; Dash et al., 2017b; Goodbody et al., 2016; Kachamba et al., 2016; Morley et al., 2017; Puliti et al., 2015; Wallace et al., 2012). Several reviews have summarised aspects of UAV research in a range of contexts including environmental monitoring (Manfreda et al., 2018), forestry (Torresan et al., 2016), ecology (Anderson and Gaston, 2013), and other domains (De Roos et al., 2018; Singh and Frazier, 2018). However, no review has yet addressed the application of UAV data to support IAP research even though these data are well suited to this application. We sought to develop a clear understanding of the current state of knowledge and to identify research needs to guide further development of UAVs as a tool for IAP research and management.

In this paper, we reviewed the research on UAV deployment for collection of remotely sensed data for IAP research. We illuminate current trends and identify additional research that would aid progress. Specifically, we provide information on the characteristics of the study system, analytical methods, technical configuration, and limitations of all studies. This was completed through a comprehensive review of studies on the topic and the authors' knowledge in this area from previous experience.

3.4 Methods

We collated research into IAP remote sensing and on the use of UAVs in the context of IAPs. This was achieved through a series of nested search queries in the Scopus and ISI web of science databases. The results were cross-referenced against Google Scholar to identify any studies missed initially. The search strings used featured a selection of terms compiled by the authors, and with reference to the techniques presented by Vaz et al. (2018a). This identified studies containing these terms in the keywords, title, or abstract. Following a review of the first ten records returned within each query the search terms were updated to include several new or alternative terms (Table S1). The initial query was designed to return all IAP studies found within the databases. Subsequently, two further queries were designed to 1) restrict the IAP research to only those studies that employed remote sensing of any kind, and 2) to identify which of these studies used UAVs for data collection. Only English language peer-reviewed articles were included. The search timeframe was from the beginning of database records to the search date in 20 April 2019. A small number of articles were eliminated from the dataset as they were not relevant to the aims of this review.

The full text of each UAV-based IAP study was reviewed to enable categorisation following a procedure adapted from Vaz et al. (2018a). Studies were categorised according to (A) the taxonomy of the IAP and characteristics of the habitat under invasion, (B) properties of the UAV data collection in the study, (C) the analytical methodology followed, and (D) the limitations identified (Table 3.1).

3.5 Literature Review

A total of 309 IAP records were returned when all remote sensing platforms were considered; only 24 of these featured UAV as a data collection platform. The first IAP studies using remote sensing were published in 1999. Thereafter, there was a steady annual increase in studies throughout the early 2000s, which stabilised during the latter part of the decade, before increasing substantially in 2017 and 2018 (Figure 3.1). This pattern is consistent with the findings of a previous meta-analysis (Vaz et al., 2018b) and includes two distinct phases. The first, between 2003 and 2007, was due to growing awareness of IAP issues and increased availability of analysis ready remotely sensed data. The second increase between 2016 and 2018 is attributable to the emergence of UAVs as a tool for IAP research and further heightening of awareness of IAP impacts.

The earliest study using a UAV for IAP was published in 2010 (Figure 3.1). There were no further studies published until 2016 and then a substantial increase between 2016 and 2018. This coincided with the widespread availability of high-quality, reliable commercial UAVs. The comparative abundance of UAV related studies in other domains (Manfreda et al., 2018) indicates the novelty of the application of UAV remote sensing to IAP studies. Clearly, there is significant scope within this domain for further research.

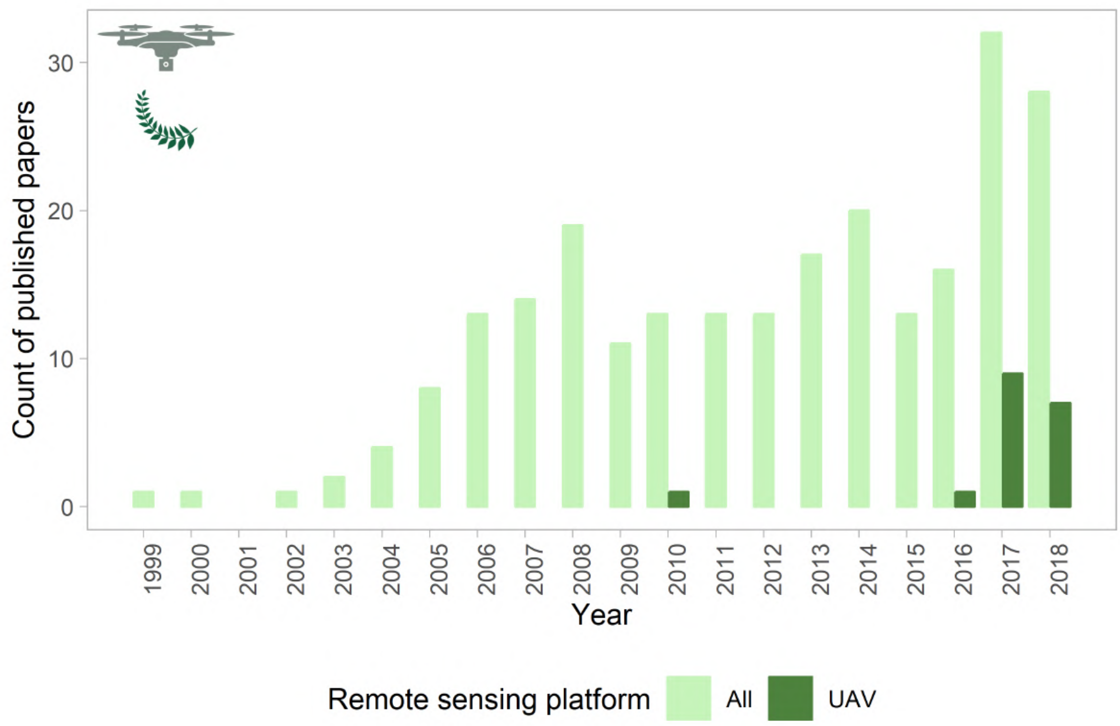

Fig. 3.1 Count of the number of published peer-reviewed articles in the Scopus database for studies using all remote sensing platforms (All) and remote sensing from a UAV (UAV) up to 31 December 2018.

Studies using UAVs for IAP research have originated throughout the world (Figure 3.2). The largest number of studies (5) originated in the USA with multiple studies from China (3), Czech Republic (3), Chile (2), and South Africa (2). Single studies have originated in other countries including Brazil, Australia, Canada, Belgium, and New Zealand.

3.5.1 Taxonomic and habitat characterisation of UAV-based IAP research

We reviewed the species and growth form of the target IAP in the published UAV studies. Herbaceous plants were most commonly targeted comprising 40% of studies. This was followed by studies targeting shrubs (20%), trees (20%), a combination of trees

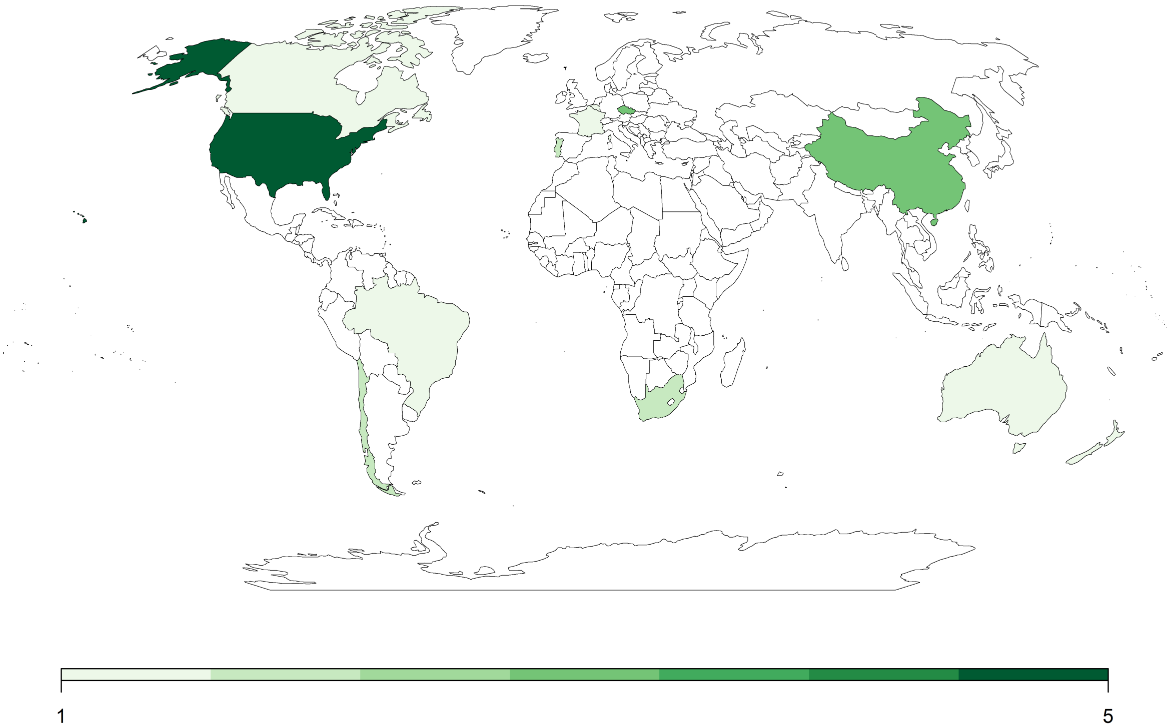

Fig. 3.2 The count of published UAV-based IAP research based on the host country of the study

and shrubs (10%), and two studies (8%) targeting succulent plants. The predominance of studies targeting herbaceous plants mirrored the all-platform remote sensing studies where 49% of studies focussed on herbaceous IAPs (Vaz et al., 2018b). There are also striking differences in the target IAP form between studies using all platforms and those that use UAVs. When all platforms were considered 44% of studies were concerned with trees (Vaz et al., 2018b) whereas for UAV studies the equivalent proportion was 20%. Earlier all-platform studies focussed on trees to facilitate the early development of classification methods using the coarser spatial resolution imagery available (Vaz et al., 2018b). Of the tree-focussed UAV-based IAP studies one addressed the detection of juvenile trees (Dash et al., 2019c), while another was concerned with an understory tree frequently hidden by the surrounding canopy (Perroy et al., 2017). The very high-resolution data available from UAVs enables focussing on smaller, and often more difficult to detect species. This is reflected by the larger proportion of shrub and herb studies in the UAV specific literature (20% and 10%) compared to the all-platform literature (3.1% and 1.5%).

The wide range of host environments is a testament to the flexible nature of UAVs and the variety of threatened environments. The pattern of environments studied is somewhat similar to the overall trend in studies using other remote sensing platforms (Huang and Asner, 2009). The earliest study using UAVs for IAP took place in an agricultural setting (Bryson et al., 2010) where the spread of IAPs can reduce productivity. Several studies have been undertaken in mixed landscapes where land uses included agricultural areas as well as forest or shrubland (Alvarez-Taboada et al., 2017; de Sa et al., 2017; Dvořák et al., 2015; Müllerová et al., 2017a, 2016). The management of invasions into vulnerable wetland ecosystems remains a focus of UAV studies in a similar manner to other remote sensing platforms. Studies in wetland environments using UAVs have originated from groups in the USA (Lishawa et al., 2017; Zaman et al., 2011) and Canada (Hill et al., 2017). These focussed on the detection of reed species (*Typha spp.* and *Phragmites spp.*) and the herb *Iris pseudacorus L.*. Due to the relative ease of separability of reed species in some wetland environment the classification accuracy reported was high and UAV-based detection and mapping has been operationalised for monitoring management activities (Lishawa et al., 2017).

IAP studies have also been located in arid, or semi-arid, environments of South Africa (Mafanya et al., 2017, 2018) and the Brazilian savanna. In the Brazilian savannah dominated by grasses and monocotyledons UAVs have been used for detection and mapping of *Acacia mangium* (Lehmann et al., 2015). The spectral and structural properties of the target tree allowed accurate separation from the indigenous shrubs and small trees present. Other habitats that have hosted UAV-based IAP studies include riverbanks and mountainous areas. The IAP *Fallopia japonica* has been mapped along the banks of two river systems in France using multi-date UAV data (Martin et al., 2018). Detection of IAP using UAVs has also been extended to mountainous areas (Wu et al., 2019) where data collection can often be complicated by shading and challenging weather. Given the high density of IAPs in cities (Gaertner et al., 2016) and their increased vulnerability to new invasions (Hulme, 2009), it is notable that there are no UAV-based studies in urban areas. This is due to stricter restrictions on low-flying UAV flights in many urban jurisdictions due to safety and privacy concerns. The study environment has a major influence on the ease of separation of the target from indigenous species. Detection accuracy is highest where the spectral or structural characteristics of the IAP are significantly different from the vegetation of the host community. In forested areas the presence of the IAP in the overstorey canopy also leads to greater higher detection accuracy.

3.5.2 Characterising UAV data collection in IAP research

UAV systems can be characterised according to the configuration of the wing that provides uplift to the airframe; these are typically separated into fixed-wing and rotary-wing craft. Fixed-wing craft have a simpler structure with efficient aerodynamics that can be configured to provide longer flying times at faster speeds. Because of the required continuous airstream, fixed-wing craft cannot remain stationary and are not suited for detailed inspection work. They also require space for take-off and landing and so can be difficult to deploy in some environments. Rotary-wing craft have more complex mechanical and electronic configurations resulting in better manoeuvrability, fine control, and resilience to turbulent air. They can take-off and land vertically but typically cannot stay airborne for longer periods due to battery limitations.

UAV-based IAP studies are divided between fixed-wing (50%) and rotary-wing (50%) platforms. There is a clear trend showing that older UAV studies used fixed-wing craft and that rotary-wing craft have become more common in recent years. This is likely caused by the ubiquity of reliable and low-cost rotary-wing craft since 2016 from commercial providers such as DJI (DJI Ltd., Shenzen, China).

The choice of craft deployed is usually a compromise between budget, the size of the area of interest, and the sensors required. Both platforms can provide very high-resolution imagery, the mean ground sampling distance (GSD) reported in the UAV studies was 4 cm for fixed-wing craft and 6 cm for rotary-wing craft. These means are skewed by a single rotary-wing study that used unusually coarse imagery (GSD = 18 cm) (Wu et al., 2019), excluding this study, the average GSD collected with rotary-wing craft was 4 cm. Only rotary-wing craft have been deployed with a laser scanner (Dash et al., 2019c) or hyperspectral cameras (Lopatin et al., 2019), but multispectral and RGB cameras have been used with both craft types. This is due to the greater flexibility, stability, and capacity for lower velocity flight of the rotary-wing craft. The more controlled vertical take-off and landing also offers greater protection for expensive sensors.

Apart from a single study (Dash et al., 2019c) all IAP studies that use UAVs have used passive sensors (Table 3.2). This is probably because of the increased cost, complexity, size, and weight of miniaturised active sensors. Six studies used RGB imagery (Bryson et al., 2010; Hill et al., 2017; Mafanya et al., 2017, 2018; Perroy et al., 2017; Wu et al., 2019) with the remainder using multispectral imagery with bands frequently including the near-infrared and red edge. Only two studies (Kattenborn et al., 2019b; Lopatin et al., 2019) used UAV-borne hyperspectral imagery but this will likely increase as miniaturised hyperspectral cameras become more accessible. A range of consumer-grade RGB cameras have been used (Table 3.2) and modifying consumer-grade cameras by replacing the inbuilt filter to capture broadband near-infrared data has been popular (Table 3.2). Narrowband multispectral cameras have been used in a small number of studies (Dash et al., 2019c; de Sa et al., 2017; Peña et al., 2013), these sensors have a finer spectral resolution offering differentiation of IAP in more complex environments. Models used to date include the Sentera Double 4k (Senterra LLC, Houston TX, USA) and the TetraCam (Tetracam Inc, Chatsworth CA, USA). Other cameras such as the MicaSense RedEdge (MicaSense, Seattle WA, USA) and its successors have been used in UAV research (Dash et al., 2018, 2017b) including IAP studies (Samiappan et al., 2017a).

Table 3.1 Categories used for the description of the published UAV-based invasive plant studies.

Category	Description
A. Taxonomic and Habitat Characterisation	
Species	The name of the species studied as listed in The Plant List (http://www.theplantlist.org/)
Growth form	The growth form of the species: herbaceous, shrubs, trees, succulents or ferns
Habitat	Targeted habitats classified based on the habitat classification scheme from IUCN (at: http://www.iucnredlist.org/)
B. Characterising UAV Data Collection	
UAV type	The type of UAV used (Fixed-wing or rotary-wing)
Sensor type	The type (active / passive), model and properties of the sensor used
GSD	The ground sample distance (GSD) of the imagery collected
Altitude	The reported data collection altitude used in the study
Area coverage	The area covered by the UAV data
C. Analytical Methodology and Study Characterisation	
Image analysis type	The type of image analysis for detection (pixel-based / object-based / phenological / hybrid)
Classification autonomy	Level of image classification autonomy used (supervised / unsupervised)
Processing software	Processing software used
Ground sampling	Characteristics of the ground sample collected (if any)
Sensor comparison	Was a sensor comparison undertaken to compare the relative efficacy of the platforms
D. Study and Operational Limitations	
Operational constraints	Operational constraints due to available technologies or other factors limiting the capacity to collect relevant data
Technical constraints	Technical and methodological approaches are the major limitations (e.g. sensor capability, data storage, computational power, processing time)
Cost	Costs of data acquisition, equipment, or processing are too expensive
Field validation	Results can only be seen as accurate if proper field calibration or validation is done
Spectral resolution	The spectral resolution of available data is insufficient to get accurate results
Spatial resolution	The spatial resolution of available data is insufficient to get accurate results
Temporal resolution	The temporal resolution of available data is insufficient to get accurate results

Table 3.2 Properties of the cameras used in UAV-based IAP research

Sensor type	Manufacturer	Model	Spectral res.	Spectral range	Spatial res.	Weight	Source
Hyperspectral	Gamaya	OXI VNIR-40	40 bands	450-950 nm	2MP	250 g	(Kattenborn et al., 2019b), (Lopatin et al., 2019)
Multispectral	Sentera	Double-4K	5 bands	416 – 760 nm	12.3 MP	80g	(Dash et al., 2019c)
Multispectral	TetraCam	Mini-MCA-6	6 bands	450 – 900 nm	1.3 MP	700g	(Peña et al., 2013)
Multispectral	MicaSense	RedEdge	5 bands	470 – 860 nm	1.3 MP	150g	(Samiappan et al., 2017a), (Samiappan et al., 2017b)
x RGB*	Canon	Powershot S100	4 bands	470 – 670 nm	12.1 MP	198g	(Dvořák et al., 2015),(Lishawa et al., 2017),(Mafanya et al., 2017), (Müllerová et al., 2016)
RGB*	Ricoh	GR3	4 bands	470 – 670 nm	24.2 MP	257g	(Michez et al., 2016)
RGB	DJI	FC350	3 bands	470 – 670 nm	12.4 MP		(Hill et al., 2017), (Perroy et al., 2017), (Wu et al., 2019)
RGB	Canon	G9X	3 bands	470 – 670 nm	20.2 MP	209 g	(Lishawa et al., 2017)
RGB*	Canon	PowerShot SD780 IS	4 bands	470 – 670 nm	12.1 MP	133 g	(Lehmann et al., 2015)
RGB	Canon	IXUS 220 HS	3 bands	470 – 670 nm	12.1MP	141 g	(Alvarez-Taboada et al., 2017)
RGB*	Canon	PowerShot ELPH 300HS	3 bands	470 – 670 nm	12.1MP	141 g	(Alvarez-Taboada et al., 2017)
RGB+*	Sony	Alpha A5100	3 bands	470 – 670 nm	24 MP	399 g	(Dvořák et al., 2015)
RGB*	Canon	IXUS/ ELPH	3 bands	470 – 670 nm	10 MP	155 g	(de Sa et al., 2017)
RGB	Sony	NEX-7	3 bands	470 – 670 nm	24 MP	353 g	(Mafanya et al., 2018)
RGB*$	Sony	Alpha 7	3 bands	470 – 670 nm	24 MP	769 g	(Martin et al., 2018)
RGB	Canon	100D	3 bands	470 – 670 nm	18 MP	407 g	(Kattenborn et al., 2019b), (Lopatin et al., 2019)
RGB	Canon	EOS 5D	3 bands	470 – 670 nm	12.8 MP	810 g	(Wan et al., 2014)

* Camera filter modified to record near-infrared. In many instances this is achieved by removal of the built-in IRcut filter and the addition of an alternative (e.g. Hoya R72) filter.
+ Additional lens (Sony E-20) used
$ Additional FE 35mm f/2.8 Zeiss lens (281 g)

The GSD provided by sensors onboard UAV platforms is related to data collection altitude. At higher altitudes, the swath width collected is larger and so a larger area is covered by each image. The area covered by each pixel is larger at higher altitudes and so the minimum size of the object that can be resolved will be larger. The size of the target plant at the life stage of interest must be carefully considered when selecting the sensor and altitude used.

The UAV-based IAP research has generally used very high-resolution imagery collected from low altitudes (mean altitude = 105 m a.g.l). This is the finest resolution imagery available for IAP research with conventional aerial imagery (typically 0.1 - 0.5 m) and satellite imagery (typically 0.5 - 250 m) being considerably coarser (Figure 3.3). This means that detection of small herbaceous plants (Lishawa et al., 2017), understory trees (Perroy et al., 2017), and immature trees (Dash et al., 2019c) are possible. The maximum reported altitude used for UAV data collection was 160 m agl (Mafanya et al., 2018). Higher altitudes can be achieved from UAVs and regularly are where photogrammetric methods are used over forest canopies (Goodbody et al., 2019; Puliti et al., 2020). A coarser resolution can be advantageous to the image matching process, but legislative restrictions aimed at protecting commercial air space limit operational altitude used.

The maximum range of most UAVs is limited by battery capacity restricting the area surveyed in a single flight. With repeated surveys large areas can be covered but this can be time and cost prohibitive. Furthermore, changes in atmospheric and lighting conditions can reduce the consistency of the data collected during subsequent flights. Progress in forest resource assessment has developed sampling methods that link UAV data to other data sources (Puliti et al., 2017b). This has now been extended to IAP research where initial methods have been developed for extrapolating UAV derived findings to large areas using satellite imagery (Kattenborn et al., 2019b). Further

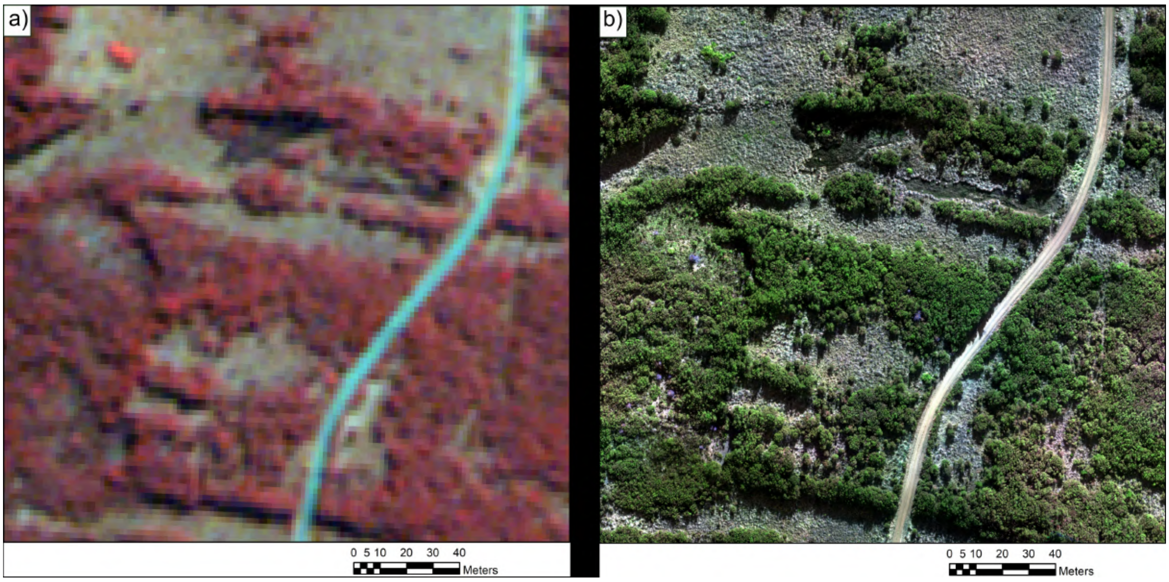

Fig. 3.3 Imagery of an area invaded by invasive alien plants amongst various other plant species. The comparison shows imagery from (a) the WorldView-2 multispectral sensor (spatial resolution = 1.8 m) and (b) UAV imagery (spatial resolution = 0.06 m). WorldView-2 is amongst the highest spatial resolution satellite sensors but the UAV imagery affords a more detailed depiction of plant species composition.

research is required to enable UAV data to progress this as the optimal methods and data source will vary according to the local conditions, satellite data availability, and the properties of the target plant.

The average size of the area assessed using UAV for IAP detection was 246 ha (range = 1.4 ha – 1450 ha). This varied according to UAV configuration between rotary-wing craft (mean = 200 ha) and fixed-wing craft (mean = 310 ha). In some scenarios, this is a suitable operational scale but in other contexts, this is not large enough and UAV data must be augmented. As UAV technology advances and modern communications systems enable safer working practices, we expect these areas to increase. This will be facilitated by improvements in power source, lighter aircraft with greater payload capacity, and increased range of radio control systems.

3.5.3 Analytical Methodology and Study Characterisation for UAV-based IAP research

Analytical approaches

Image classification can be separated into pixel-based and object-based image analysis (OBIA) depending on whether individual pixels or groups of pixels (objects) within the image are considered the fundamental unit of classification (Dronova, 2015; Li et al., 2014). Since the earliest remote sensing studies, pixel-based image analysis has been the mainstay of automated image classification (Duro et al., 2012), although more recently OBIA has become increasingly popular (Blaschke, 2010). Several studies have compared the two methods (Castillejo-González et al., 2009; Cleve et al., 2008; Duro et al., 2012; Whiteside et al., 2011; Yu et al., 2006) and have frequently found OBIA to be more accurate (Xu et al., 2017); but this is not true in all cases (Duro et al., 2012). A UAV-based IAP study (Mafanya et al., 2017) compared both methods and found that the accuracy was similar. However, the OBIA method tested was found to accurately map both small and large clumps of the target plant and the authors recommended this approach (Mafanya et al., 2017). The UAV studies concerned with IAP are quite evenly split between pixel-based (45%) and object-based (55%). Studies using both methods report high classification accuracy and there is no clear difference between the two. Manual image interpretation provides an alternative to automated image classification. The amount of imagery that can be interpreted and therefore the area that can be manually processed is limited by the endurance of the human interpreter. Nevertheless, manual interpretation provides a useful approach for IAP detection in targeted studies, especially where scene complexity is high (Perroy et al., 2017).

Regardless of the type of image classification used, an algorithm for classifying the fundamental analytical unit is required to output maps. These algorithms can be supervised or unsupervised and a wide range of parametric and non-parametric classification algorithms have been developed (Lu and Weng, 2007; Phiri and Morgenroth, 2017). Both algorithm types have been successfully applied in published studies but non-parametric methods such as support vector machines (SVM), random forests (RF), and artificial neural networks (ANN) have become popular. The key advantages of these approaches are freedom from assumptions about the distribution of the underlying dataset and evidence for improved classification performance in more complex landscapes (Lu and Weng, 2007; Phiri and Morgenroth, 2017; Rodriguez-Galiano et al., 2012).

In UAV-based IAP studies classification procedures range from simplistic rule-based thresholding (Lishawa et al., 2017; Peña et al., 2013) to statistical learning approaches (Müllerová et al., 2017a; Samiappan et al., 2017a). The most commonly used classifier RF (Breiman, 2001) was used in 33% of studies. This algorithm has been shown to be highly flexible and capable of producing accurate results in many domains (Dash et al., 2015, 2017b; Mellor et al., 2013). The next most popular algorithm (SVM) was used in 17% of studies. Rule-based spectral classification was a popular approach and a single study has trialled classification based on machine vision (Bryson et al., 2010). Maximum Entropy One-Class Classification has also been trialled (Kattenborn et al., 2019b; Lopatin et al., 2019). This approach has the advantage of only requiring the analyst to identify a single class "positive" sample to train the algorithm, saving considerable field or manual interpretation time. Future research will benefit from the development of new methods using deep-learning algorithms that will become powerful tools for IAP detection using the spectral and textural properties of UAV imagery.

Analytical software

We reviewed the processing software used to assist method development for future studies. Two types of software are typically required for processing UAV imagery 1) pre-processing software that provides geo-rectification, ortho-mosaicing and bundle adjustment outputting analysis-ready data, and 2) analysis software for segmentation and image classification.

Pre-processing of UAV imagery has recently advanced through the development of commercial software that produce 3D point clouds, digital surface models (DSM), and enable orthomosaicing of UAV imagery using dense overlapping imagery. This technique allows 3D reconstruction of a scene using 2D images through feature detection, image matching, and bundle block adjustment (Mafanya et al., 2017; Wang et al., 2014). Ground control points (GCP) identified by the user can also be integrated with the geotagged raw UAV imagery to provide a georectified orthomosaic suitable for image classification (Mafanya et al., 2017). Two software packages are widely used in the UAV-based IAP research, with Photoscan (Now renamed Metashape) (Agisoft LLC, St Petersburg, Russia) the most popular followed by Pix4D (Pix4D S.A., Lausanne, Switzerland). The popularity of Photoscan is due to the lower price, ease of scripted batch processing, and superior performance over vegetated areas (Sona et al., 2014). Open source alternative (e.g. https://www.opendronemap.org/) also offer high quality pre-processing of UAV data free of charge.

Following generation of analysis-ready imagery, software is required for subsequent image classification. For automated classification, the most popular software is eCognition (Trimble LLC, Sunnyvale CA, USA), which provides a user interface for the OBIA methods initially proposed in the 1970s (Kettig and Landgrebe, 1976). Although numerous other commercial OBIA software exists, these have not been used in

UAV-based IAP research. Several studies have made use of open source programming languages such as R (R Core Team, 2018) and Python (Foundation, 2018).

Field sampling

Field sampling is an important part of remote sensing research as these data are used to train classifiers and validate classification outputs. Various strategies have been proposed for the collection of a field sample which is a significant expense and, if not carefully designed, can introduce bias (Cacho et al., 2006; Kaplan et al., 2014). Some studies have sought to minimise or eliminate ground-based data collection from their study design (Kattenborn et al., 2019b; Lopatin et al., 2019; Piiroinen et al., 2018). Whilst more cost-effective without an appropriate field sample the error rates of the methods examined cannot be quantified. This is exacerbated for IAPs that are difficult to detect using remotely sensed imagery alone as even the most careful manual image interpretation can include substantial errors.

The majority (90%) of UAV-based IAP research included ground sampling and a range of sampling strategies were employed. Probability-based field sampling is deemed to be best practice (Olofsson et al., 2014; Watt et al., 2015) but only a minority (23%) of UAV-based IAP research used these approaches. The most popular probability-based approach used was stratified sampling using pre-existing remotely sensed data (de Sa et al., 2017; Mafanya et al., 2017; Müllerová et al., 2016; Wu et al., 2019). This improves sampling efficiency whilst ensuring an unbiased sample with a known probability of inclusion in the field sample. Most studies used selective sampling targeting specific plants or land use types.

The sampling unit used in UAV-based IAP research was most commonly point (Alvarez-Taboada et al., 2017; Mafanya et al., 2017; Müllerová et al., 2016) or individual plant sampling (Dash et al., 2019c; Perroy et al., 2017). Other studies incorporated sampling of plant traits (de Sa et al., 2017; Peña et al., 2013). Supplementary data can provide context on the host growing environment (Dash et al., 2019c; Perroy et al., 2017). One innovative study quantified the target plant's growing environment using hemispherical photographs enabling the detectability of an understorey IAP to be linked to the surrounding canopy development (Perroy et al., 2017).

In modern studies, the collection of global navigation satellite system (GNSS) data is common practice. Within the UAV-based IAP research, GNSS data were recorded in 88% of studies where a field sample was collected. Both recreational-grade and specialist survey-grade GNSS equipment were used. Recreational-grade data were commonly used (Dvořák et al., 2015; Hill et al., 2017; Lehmann et al., 2015; Müllerová et al., 2016) and have a reported accuracy of approximately 10 m. These data are faster to collect and require less specialist equipment and software. Several studies used survey-grade equipment with positional correction made through post-processing or through real-time kinematic (RTK) methods (Dash et al., 2019c; de Sa et al., 2017; Mafanya et al., 2017; Martin et al., 2018; Perroy et al., 2017; Samiappan et al., 2017a,b). This provides accuracy of less than 1 m minimising positional errors in the field sample.

In addition to positional data, information on plant traits can provide useful information to characterise invasions and the causes of variable detection success. Plant traits that have been collected in UAV-based IAP studies included target plant dimensions (Dash et al., 2019c; Lehmann et al., 2015; Perroy et al., 2017), flower counts (de Sa et al., 2017), and identification of the onset of seed production (Dash et al., 2019c).

3.5.4 Study and Operational Limitations Identified

Study limitations identified in UAV-based IAP research were collated and classified (Table 3.1). This provided suggestions for future research direction and a comparison with limitations identified in the all-platform IAP research. The most cited limitations in the UAV-based IAP literature were operational and technical constraints with almost all studies (95%) citing these. The most frequently reported was limited flight time and resulting difficulties in acquiring data over larger areas. This limitation is caused by constraints on the operational range due to battery performance, payload weight, and craft configuration (Alvarez-Taboada et al., 2017; Dash et al., 2019c; Mafanya et al., 2018; Martin et al., 2018).

The area range of UAV data collection is also limited by legal restrictions that prevent operation beyond the visual line of sight (BVLOS) of the pilot or restrictions on flight altitudes. In forests, this is problematic as trees disrupt the line of sight to the craft (Perroy et al., 2017). This is exacerbated by altitude restrictions designed to exclude UAVs from commercial airspace. Furthermore, legal restrictions around where UAVs can operate prevent their use in some of the most sensitive areas for IAP research. Urban areas are often under the greatest pressure from IAPs and are the focus of considerable monitoring and management activity (Pyšek, 1998; PyšEK and Hulme, 2005). Unfortunately, UAV use in this environment is strictly regulated if allowed at all (Müllerová et al., 2017a)(Müllerová et al., 2017a). The impact of adverse weather conditions on UAV operation and data collection is also an operational constraint (Martin et al., 2018) as they cannot operate in heavy winds and data collection during precipitation is not feasible.

Due to the operational limitation of data collection altitude and the miniaturisation of the onboard sensors, the swath covered by a single UAV image is relatively small. Therefore, many images are required to cover a study area leading to high computation requirements and extended processing times (Mafanya et al., 2017; Müllerová et al., 2016). Other common technical limitations raised include GNSS accuracy of both field survey and UAV positioning (de Sa et al., 2017; Hill et al., 2017; Lehmann et al., 2015;

Mafanya et al., 2017), the inability of passive UAV sensors to penetrate non-target canopy to identify IAPs in the understory (de Sa et al., 2018; Mafanya et al., 2017; Müllerová et al., 2017b; Perroy et al., 2017; Wu et al., 2019), and the lack of established software for analysis of UAV data without expert user input (Lehmann et al., 2015; Martin et al., 2018; Perroy et al., 2017).

The high cost of emerging technologies often limits research uptake and must be considered when recommending practical solutions. Costs can accrue through the initial financial outlay for purchasing hardware, purchasing software, data storage and computing hardware, and through labour-intensive activities such as field measurement. Fortunately, the purchase cost of UAVs has decreased in recent years inversely to their sophistication. Most early studies used custom-built craft, and these are prohibitively expensive for most practical applications (Lehmann et al., 2015). More recently most studies have transitioned to using standard commercial UAVs for data collection bridging the gap towards practical solutions.

The price of the miniaturised UAV sensors has been noted as a constraint. Laser scanning systems offer accurate vegetation characterisation and a method for detecting IAPs in the understory. However, purchasing and operating these systems is expensive limiting current uptake (Martin et al., 2018; Perroy et al., 2017). In a similar manner, the finer spectral resolution of hyperspectral cameras is favourable for differentiating IAPs (Martin et al., 2018; Müllerová et al., 2017a) but they remain prohibitively expensive. Cost limitations mean that many studies have used modified consumer-grade cameras rather than specialised narrowband multispectral sensors. This has led to issues with spectral differentiation (Lishawa et al., 2017), blurring and distortion (Lehmann et al., 2015; Müllerová et al., 2017a), and issues caused by changing illumination during data collection (Dvořák et al., 2015). However, it should be noted that converting to purpose built multispectral cameras does not guarantee that image quality issues will be resolved.

Using UAVs in IAP research can lead to reduced field measurement. This is beneficial as costs are reduced, technicians are less exposed to danger, and damage or disturbance to indigenous ecosystems is minimised. However, at least during method validation, ground-based field datasets remain important. The limitation caused by a lack of an adequate field sample or training dataset has been noted (Michez et al., 2016), but others have sought to develop methods to eliminate the need for a ground-based field dataset (Lopatin et al., 2019). Depending on the specifics of study design and the purposes of the study, research without a robust field dataset may be deemed to be less reliable.

No UAV-based IAP study identified spatial resolution as a limitation. This contrasts with the all-platform research where studies published since 2000 consistently identified spatial resolution as a limitation (Vaz et al., 2018a). This suggests that this technology has solved the issue of spatial resolution in IAP research. However, very high-resolution imagery is not always advantageous for image classification as it can mask the distinctive spatial properties of the object of interest when using OBIA (Müllerová et al., 2016). This can happen when the plant traits that are useful for detection, such as branching patterns or leaf architecture are saturated by noise resulting from the very high-resolution imagery. Approaches using deep learning methods may resolve these issues and are an active area of research in UAV-based IAP research. The temporal resolution of the imagery available is less of a limitation in UAV-based IAP research than in the general remote sensing research. UAV deployment flexibility and their capacity for data collection under overcast conditions means that the return frequency can be higher. However, additional data collection incurs significant financial costs, and this may be prohibitively expensive. Spectral resolution remains a significant limitation for

UAV-based studies. This is most common in studies using modified consumer-grade cameras (Dvořák et al., 2015; Lehmann et al., 2015; Lishawa et al., 2017; Müllerová et al., 2017a) although has also been noted for multispectral imagery (Peña et al., 2013).

3.6 Discussions

3.6.1 Overall trends emerging

The application of UAVs for IAP research is expanding rapidly throughout the world. These studies have adapted methods from other remote sensing platforms to the new opportunities provided by the proliferation of UAVs. Although the traditional limitations of spatial and temporal resolution have been solved, others remain, and ongoing research must seek solutions to these. Several of the limitations identified require advances in hardware to resolve. For example, if legal restrictions are loosened, the areal coverage of UAV data will be solved through improving battery performance and craft design. The data processing pipelines to produce analysis-ready data and to automatically detect IAP in UAV imagery is currently a bottleneck to further research. We have scanned emerging technologies to highlight solutions that might overcome the identified limitations.

3.6.2 Emerging technologies that can reduce the impact of the identified limitations

The most frequently cited limitation to UAV-based IAP research was the data collection longevity. Innovation in the UAV sector is rapid and several new-to-market, or near-market innovations may overcome current limitations. These include craft with better aerodynamic efficiency, including vertical take-off and landing (VTOL) that combine the flexibility of rotary-wing and the efficiency of fixed-wing craft. These are now commercially available (e.g. https://www.altiuas.com) and reportedly offer up to 20 hours flight time, a substantial improvement on widely used rotary-wing systems that offer around 20-30 minutes. The power sources used must advance as the batteries currently used are at their performance limit and so flight times have not kept pace with other system aspects. The commercialisation of alternative power sources such as hydrogen fuel cells could considerably improve performance (McConnell, 2007). Several studies have configured hydrogen fuel cell UAVs (Okumus et al., 2017; Ward and Jenal, 2010) and reported a flight endurance of more than 24 hours when carrying up to 3 kg (Swider-Lyons et al., 2011). Hybrid power systems using a combination of petroleum-based fuel and batteries offer an alternative and are now available (e.g. https://skyfront.com/). In-flight battery charging by wireless power transmission is also being developed (e.g. (Simic et al., 2015)). Improved power provision will facilitate the emergence of longer-range UAV and overcome the major limitation identified in the UAV-based IAP research.

Legislation governing UAV operation remains a significant challenge in many regions. Legal frameworks governing UAV use have been developed since the early 2000s and vary considerably in operational restrictions (Stöcker et al., 2017). The major legislative changes needed to address the limitations identified are the permission of BVLOS operation and relaxation of the maximum operating altitude. Technological advances including automated collision avoidance systems will contribute to increasingly safe operation and should promote relaxation of the legal restrictions. There is a push towards unmanned traffic management systems (UTMS) (Jiang et al., 2016) to better control UAV traffic and the advent of mandatory automatic dependence surveillance-broadcast (ADS-B) transmitters onboard UAVs should encourage relaxation of restriction on BVLOS operation.

Computing power has increased exponentially over the last decade and both storage and computational capacity are becoming cheaper. Therefore, the costs of compute intensive pre-processing and analytical aspects of UAV-based IAP research are decreasing. Meanwhile, the need for conventional computing is likely to be reduced by the further development of machine vision methods that enable close to real-time detection without the requirement for pre-processing (Bryson et al., 2010). This may enable automatic adjustment of search patterns for a more targeted search, improving the probability of detection of rare or partially obstructed IAP. Removing the need for input from an analyst and complex pre-processing means that one of the key technical limitations identified will be eliminated.

Several studies identified GNSS accuracy as a limitation. The negative effects of this limitation can be reduced through using survey-grade GNSS systems with sufficient occupancy to provide a high accuracy positional fix. Recent developments, including the launch of the European Union's Galileo Navigation System, will improve GNSS accuracy and complement alternative systems such as the Global Positioning System (GPS) and the Global Navigation Satellite System (GLONASS). However, poor GNSS accuracy from field data collection under dense vegetation remain problematic.

The cost of sensor and UAV hardware will reduce as the market for these technologies matures. Researchers can speed development by identifying the best and most cost-effective solutions that are relevant for IAP research. Despite their proven utility, the cost of both hyperspectral sensors and laser scanners have been highlighted as prohibitively expensive. The advent of lower cost "snapshot" UAV hyperspectral systems and their application to natural resource monitoring will go some way to addressing the cost limitation (Aasen et al., 2015; Saarinen et al., 2018a; Yue et al., 2018; Zhong et al., 2018). These systems are also easier to use than traditional pushbroom sensors, particularly when mounted on UAVs where positional data may be less accurate (Adão et al., 2017).

Laser scanning systems provide the most accurate depiction of vegetation structure and terrain characteristics available and can be valuable for IAP research. Systems that provide high-quality solutions for UAVs are becoming more ubiquitous and show promise. Unfortunately, the price of survey-grade units remains expensive, but following developments in other domains it is likely that costs will decrease as they become more widespread. The emergence of laser scanning systems that can also collect spectral data (Wang et al., 2018) offers an exciting tool for IAP research through the provision of highly detailed structural and spectral data from a UAV potentially enabling IAP detection in highly complex environments.

3.7 Conclusion

We have reviewed the current state of the studies using UAV for IAP research. Our review of this rapidly developing field has identified a wide range of studies in varied biological systems throughout the world. We have summarised the limitations identified in the current research and identified emerging solutions that can help to mitigate the impact of these limitations. In this manner, we have identified niches for additional research that can further develop UAVs as a tool to support IAP research and management.

3.8 Acknowledgements

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3.9 Data availability

The search terms used to extract all records summarised in this review are included as supplementary materials. This data has also been published online and can be accessed at the following DOI 10.6084/m9.figshare.9758720.

3.10 Author contributions

JPD conceived of this review, carried out all analysis, and wrote the original draft of the manuscript. All other authors reviewed, edited, and made contributions to the text of the final version.

Chapter 4

Early detection of invasive exotic trees using UAV and piloted aircraft multispectral and lidar data

4.1 Preface

The potential of UAV data to exploit a specific niche in invasive conifer detection is clear from the review presented in Chapter 3. A particular advantage of this datatype is the capacity for flexible and regular data collection and for collecting ultra-high-resolution data. The properties of these datasets mean that for the first time very early detection of invasions may be possible. This is critical for invasive conifer control efforts as the possibility of detecting early colonisers prior to the onset of coning is vital. This led to the formulation of RQ1 in this thesis, the research presented in this chapter was designed to produce a new dataset to answer this question. Ultra-high-resolution imagery was exploited to develop methods for the detection and monitoring of invasive exotic conifers using ALS and multispectral data collected from both a UAV and a piloted aircraft at a single study site. Supervised classification methods were examined as these can provide accurate pixel level classification in relatively simple detection environment. A range of classification methods were tested with the objective of identifying an efficient means of detection at this site. An extensive field dataset was collected and used to make a detailed examination of the error rates associated with classifiers developed from all available datasets in this environment. In places a more detailed description of various components of the methods deployed is also included.

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4.2 Abstract

Exotic conifers can provide significant ecosystem services, but in some environments, they have become invasive and threaten indigenous ecosystems. In New Zealand, this phenomenon is of considerable concern as the area occupied by invasive exotic trees is large and increasing rapidly. Remote sensing methods offer a potential means of identifying and monitoring land infested by these trees, enabling managers to efficiently allocate resources for their control. In this study, we sought to develop methods for remote detection of exotic invasive trees, namely *Pinus sylvestris* and *P. ponderosa*. Critically, the study aimed to detect these species prior to the onset of maturity and coning as this is important for preventing further spread. In the study environment in

New Zealand's South Island, these species reach maturity and begin bearing cones at a young age. As such, detection of these smaller individuals requires specialist methods and very high-resolution remote sensing data. We examined the efficacy of classifiers developed using two machine learning algorithms with multispectral and laser scanning data collected from two platforms - piloted aircraft and unpiloted aerial vehicles (UAV). The study focused on a localised conifer invasion originating from a multi species pine shelter belt in a grassland environment. This environment provided a useful means of defining the detection thresholds of the methods and technologies employed. An extensive field dataset including over 17,000 trees (height range = 1 cm to 476 cm) was used as an independent validation dataset for the detection methods developed. We found that data from both platforms and using both logistic regression and random forests for classification provided highly accurate (kappa < 0.996) detection of invasive conifers. Our analysis showed that the data from both UAV and piloted aircraft were useful for detecting trees down to 1 m in height and therefore shorter than 99.3 % of the coning individuals in the study dataset. We also explored the relative contribution of both multispectral and airborne laser scanning (ALS) data in the detection of invasive trees through fitting classification models with different combinations of predictors and found that the most useful models included data from both sensors. However, the combination of ALS and multispectral data did not significantly improve classification accuracy. We believe that this was due to the simplistic vegetation and terrain structure in the study site that resulted in uncomplicated separability of invasive conifers from other vegetation. This study provides valuable new knowledge on the efficacy of detecting invasive conifers prior to the onset of coning using high resolution data from UAV and piloted aircraft. This will be an important tool in managing the spread of these important invasive plants.

4.2.1 keywords

Bio-security; Lidar; Invasive plants; Random forest; Logistic regression; Drones; RPAS; Invasion monitoring; Invasive alien plants; Multispectral.

4.3 Introduction

Conifers are amongst the most economically important tree species on Earth forming the basis of major forest industries and contributing substantially to the global annual timber yield (Farjon and Farjon, 2008). Exotic conifer plantations form the cornerstone of the plantation forestry sector in many Southern hemisphere countries. These forests provide significant economic(Dash et al., 2019a; Watt et al., 2017), social (Yao et al., 2014), and ecological benefits (Brockerhoff et al., 2008; Stephens and Wagner, 2007) and contribute significantly to global carbon sequestration (van Minnen et al., 2008; Winjum and Schroeder, 1997). Furthermore, these forests are critical in supplying the increasing fibre demands of the Earth's growing population (Payn et al., 2015). The values provided by plantation forests in many countries are widely recognised, but when planted in inappropriate areas, this valuable land use can have deleterious effects at a local scale. Many conifer species have evolved to exploit a variety of ecological niches which makes them highly suited as fast-growing plantation species. Unfortunately, the same traits also make them highly invasive in some environments (Farjon and Farjon, 2008) as they may out-compete indigenous vegetation. The prevalence of invasions by non-native invasive plants has considerable consequences in many environments and is a significant, and increasingly common, challenge for land managers (Nunez et al., 2017; Richardson et al., 2014). This is particularly true in mountainous areas where increasing levels of anthropogenic disturbance coupled with a changing climate are expected to trigger an increase in the abundance of invasive plants, and upward expansion of exotic invasive species in vulnerable mountainous regions (Dainese et al., 2017). Historically, trees did not feature prominently in global lists of important invasive plants (Richardson et al., 2014), but more recently the invasive and unfavourable nature of many tree species has been recognised (Rejmánek, 2014; Rejmánek and Richardson, 2013; Richardson and Rejmanek, 2011). Now, many tree species are included in databases of the most widespread and damaging plants (Richardson and Rejmanek, 2011).

In New Zealand, a few conifer species constitute the vast majority of the plantation forestry industry contributing significantly to the country's economic and social well-being. The forestry sector contributes almost NZ$ 5 billion in export earnings to the economy per year and directly employs some 18,000 people (NZFOA, 2016). Despite these benefits, several exotic conifer species have become invasive and are invading natural, and semi-natural, grass and scrubland habitats (Ledgard, 2003). These invasions have ecological, economic, and cultural implications within many ecosystems (Peltzer, 2018). Exotic conifers have invaded large areas in both North and South Islands primarily in grassland and shrubland areas (Howell and McAlpine, 2016; Ledgard, 2009). The area affected by invasive conifers is estimated to be 1,700,000 ha, an area approximately equivalent to the national plantation estate, and this area is thought to be increasing at 5-6 % per year (Anon., 2011).

The negative implications of this infestation are considerable, and to control, or at least slow, their spread, detection and eradication methods are required. A range of chemical and physical control methods are available, but to be effective these require accurate detection methods so that they can be targeted efficiently. For control efforts, identifying juvenile trees before they reach maturity is of considerable importance to prevent further spread. This complicates detection solutions because the ease of detection is dependent on the density of the infestation, size of the individuals present

(Dash et al., 2017a), and the complexity of the terrain and vegetation structure in the area of interest (Andrew and Ustin, 2008). In New Zealand, current surveillance and monitoring methods rely on manual conifer detection across larger areas using helicopter-based surveys by skilled operators (Woods, 2003), ground surveys in very small areas, or combinations of both (Cochrane and Grove, 2013). Detection success using current approaches is highly variable, and detailed surveillance across national or regional scales is not feasible due to high costs and resource limitations. The information void caused by a lack of an effective method for detection of invasive conifers is a major hindrance to the development of effective control procedures.

Remote sensing potentially provides a means for accurate invasive conifer detection over large areas with varied terrain and vegetation types. Automated and semi-automated techniques have been widely used to detect and monitor invasive plants in numerous environments (Hall and Asner, 2007; Hestir et al., 2008; Piiroinen et al., 2018; Underwood et al., 2003). However, research into the detection and monitoring of invasive conifers is limited. Recent research has developed a method for invasive conifer detection by classifying airborne laser scanning (ALS) returns from invasive conifers by combining ALS data with aerial imagery (Dash et al., 2017a). However, these methods have only been tested in a single vulnerable habitat type and for detection of mature trees. Further research is required to test methods in other settings using data from alternative platforms, and to extend the methods to juvenile trees. High-resolution aerial imagery has recently been used to accurately classify invasive plants including mature conifers in Chile (Lopatin et al., 2019) and New Zealand (Sprague et al., 2019). However, no research has addressed the issue of identifying invasive trees prior to, or immediately after, the onset of coning when the spread may be controlled more efficiently. Other relevant research comes from the boundary of the boreal and Arctic ecotones (Hantson et al., 2012; Næsset and Nelson, 2007; Rees, 2007; Stumberg et al., 2014a, 2013; Thieme et al., 2011) where there is considerable interest in monitoring changes in the tree line that are associated with climate change. However, there are considerable differences in environmental conditions between Scandinavia and New Zealand and so specialised techniques must be developed in both areas. In particular, the Scandinavian research frequently targets detection of all trees in the area of interest as the presence of any trees represents a shift in vegetation type. This is unsuitable in New Zealand as detection techniques must differentiate invasive conifers from non-target trees and shrubs in many environments.

A range of active and passive remote sensing technologies have been shown to be useful for the detection and monitoring of invasive exotic, or pioneer, trees in studies around the world. These studies include the use of ALS data either alone (Thieme et al., 2011) or in combination with spectral data (Dash et al., 2017a; Næsset, 2009; Stumberg et al., 2014b, 2013). The use of passive remote airborne or space-borne sensors for monitoring plant invasions is much more common (Homer et al., 2012; Piiroinen et al., 2018; Pouteau et al., 2011; Singh and Glenn, 2009; Zimmermann et al., 2011). The efficacy of these approaches is dependent on the selection of the appropriate sensor and platform that can provide imagery at the appropriate spatial, spectral, and temporal resolution to separate the target plant species from its surroundings. Data fusion refers to the integration of remotely sensed datasets to provide insight into the properties of target objects. In a forest description context, these fused datasets frequently have greater predictive power than their constituents (Xu et al., 2015). Several studies have employed data fusion for detection and monitoring of invasive plants to enhance the separability of the target organism in its environment. Combining the structural information from ALS data with spectral data from hyperspectral or multispectral imagery has proved to be particularly useful for differentiating target organisms from non-target objects (Barbosa et al., 2017; Dash et al., 2017a; Ghulam et al., 2014;

Hauglin and Ørka, 2016). The constituent datasets can either be sourced from the same or separate platforms depending on the study design.

The resolution of imagery used for invasive plant detection ranges from low spatial resolution datasets such as MODIS (Alves Aguiar et al., 2010) which have limited utility for invasive plant detection to studies using ultra high resolution imagery collected from unpiloted aerial vehicles (UAV)s (de Sa et al., 2018; Kattenborn et al., 2019b; Mafanya et al., 2017; Perroy et al., 2017). A range of satellite products have been used in studies monitoring exotic plant invasions. These range from studies moderate resolution sensors such as Landsat (spatial resolution = 30 m) (de Sa et al., 2017; Oliphant et al., 2017; Schneider and Fernando, 2010), and high spatial resolution sensors such as WorldView 2 (spatial resolution = 0.5 m) (Lantz and Wang, 2013) and Pleaides 1A (spatial resolution = 0.5 m) (Khare et al., 2017; Ng et al., 2017). Higher resolution imagery collected from conventional piloted aircraft has been widely used for invasive plant detection. These studies include a range of sensors including multispectral (Bhattarai and Cronin, 2014; Dronova et al., 2017; Mirik et al., 2013b) and hyperspectral imagery (Amaral et al., 2015; Calviño-Cancela et al., 2014; Chance et al., 2016; Ishii and Washitani, 2013; Mirik et al., 2013a; Skowronek et al., 2017a,b) but none of these studies have focused on small juvenile plants.

In more recent years, the emergence of ultra high resolution data collected from UAVs, and their application to forest monitoring (Dash et al., 2018, 2017b), has allowed the spatial resolution and threshold size of targeted invasive plants to be reduced. This potentially enables the detection and monitoring of earlier invasion stages and smaller plants to be detected. These platforms and associated miniaturised sensors have also significantly reduced the cost and improved the flexibility of acquisition of detailed remotely sensed data (Heaphy et al., 2017). Studies using UAVs for detection of invasive plants have emerged in recent years from Africa (Mafanya et al., 2017), North America (Lishawa et al., 2017; Perroy et al., 2017), South America (Lehmann et al., 2017; Lopatin et al., 2019), and Europe (Alvarez-Taboada et al., 2017; de Sa et al., 2018; Dvořák et al., 2015; Martin et al., 2018) with encouraging initial results.

The earliest UAV based studies were undertaken in an agricultural setting and made use of computer vision to identify weeds (Bryson et al., 2010). Significant knowledge gaps remain and further methodological research is required to develop the promise of these early studies as technical constraints are increasingly cited as a major factor limiting the success of remote sensing assisted invasive plant management (Vaz et al., 2018a). Furthermore, no studies have sought to develop UAVs specifically as a tool for the early detection of plant invasions (Juanes, 2018), and this capability is critical to assist with the eradication of invasive conifers from protected areas. Despite the significant body of research into the detection and monitoring of invasive plants, we are unaware of any studies that focus on detection of invasive trees during the juvenile phase of development either before or immediately after the onset of reproductive maturity. This is critically important and represents a significant challenge as coning can occur very early for some species in many environments, meaning that target objects can be very small. Furthermore, no research has directly compared the efficacy of combinations of spectral and ALS datasets obtained from UAV (UAV-LS) and piloted airborne platforms.

In this research, we seek to define the detection threshold and to characterise errors for invasive tree detection in a relatively simplistic grass and shrubland setting. We also examine the efficacy of two different classification approaches in this context and compare the predictive power of combined datasets, containing information from both multispectral and laser scanning, with data provided by single sensors.

4.4 Materials and Methods

A schematic diagram illustrating the methods used in this paper is included below (Figure 4.1). Briefly, two sets of remotely sensed data collected from a UAV and piloted aircraft platform were used alongside a manually digitised training data set defined in a Geographical Information System (GIS) to fit supervised classification models using either random forests (RF) or logistic regression (LR). For each classifier a total of 11 models were generated using UAV data and 9 models were constructed using piloted aircraft data, as the latter have one less band than the UAV data, using a combination of spectral, ALS data, and a combination of both data sources (Table 4.1). Using this approach, a total of 40 models were created. A k-fold cross validation (Bryson et al., 2010; Immitzer et al., 2016; Wong, 2015) was used to assess model precision based on the accuracy statistics described below.

Table 4.1 Summary of the all models developed for selection of the best performing model of each class with model performance assessed based on cross-validation statistics from the model fitting dataset.

Model ID	Features	Model class
1	Blue, Green, Red, Near-infrared, CHM height	Spectral + ALS
2	Blue, Green, Red, Red edge, Near-infrared, CHM height	Spectral + ALS
3	CHM height	ALS
4	Blue, Green, Red, Red edge, Near-infrared	Spectral
5	Blue, Green, Red, Near-infrared	Spectral
6	Blue, Green, Red,	Spectral
7	Red	Spectral
8	Green	Spectral
9	Blue	Spectral
10	Near-infrared	Spectral
11	Red Edge	Spectral

The best performing models were then selected from 12 categories that included the factorial combination of the two platforms, two classifiers and three classes of data (spectral, ALS, spectral and ALS). These 12 models were then used to make predictions about the presence or absence of invasive exotic conifers across the area of interest. These surfaces were then intersected with a completely independent validation dataset sampled from an extensive field data collected within the area of interest to calculate error statistics and to investigate the relationship between detection accuracy and tree size.

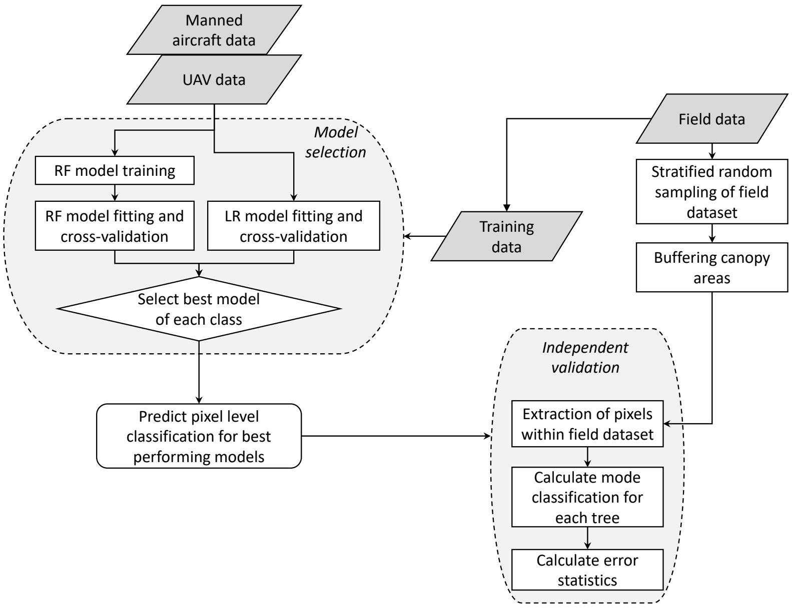

Fig. 4.1 A schematic overview of the methodology used in this research highlighting the methods for development and validation for the best performing random forest (RF) and logistic regression (LR) model for each class (Spectral, ALS, Spectral + ALS).

4.4.1 Study site

The study site is located in the Mackenzie Basin, South Canterbury, South Island of New Zealand. Topographically the area was strongly influenced by its glacial history with in-filled and now wide expanding river terraces and glacially formed rounded hills surrounded by high altitude mountain ranges. The Mackenzie Basin lies between 600-1100 m above sea level (a.s.l.) with higher slopes and hilltops also present near Lake Pukaki. The climate can be characterised as continental with dry hot summers and cold winters. The area has been dominated by native (and more recently a growing proportion of exotic) grassland species for at least the last 500 years and has been subjected to 200 years of pastoral management of varying intensities. This management combined with frequent burning, overgrazing, and incursions of rabbit outbreaks has resulted in a high level of degradation of the natural short and tall tussock grasslands and herb and shrub communities.

Sources for exotic conifers in this area have been historic plantings of shelter belts and woodlots for soil conservation, shelter, scenic, and recreational purposes across the basin. Some commercial plantings were also established over time to create a timber resource. Exotic conifer species originating from these plantings have now become invasive over thousands of hectares and the initial low densities of scattered trees are now expanding to become grassy woodlands, and even dense forested stands in some areas. The major species that have spread across most of the basin and have been controlled, but not eradicated, include *Pinus contorta* Douglas, *Pinus nigra* Arnold, *Pinus sylvestris* L., *Pinus ponderosa* Douglas, *Larix decidua* Mill., and *Pseudotsuga menziesii* (Mirb.) Franco.

The core study area used to develop and test detection methods encompassed 22.4 ha in the immediate vicinity of a shelter belt planted with a mixture of *P. sylvestris*, *P. ponderosa* and a small number of *P. nigra.* The study site is 804 m asl and is located around 11 km west of the township of Lake Tekapo (Latitude = 43° 59’ 02.2985 S, Longitude = 170° 20’ 22.43 E) (Fig. 4.2). This site was selected because it represented a first order invasion event of significantly problematic invasive conifer species within this region and provided a suitable testing ground for method development. The flat to rolling terrain of the study site represents mostly short tussock grassland, the common vegetation type in the lower parts of the Mackenzie Basin. Most common native and exotic grasses are short stature tussock species. Shrubs are mostly in the prostrate growth form, are also present and distributed sporadically throughout the area. The herbaceous component of the vegetation is dominated by exotic *Hieracium* species.

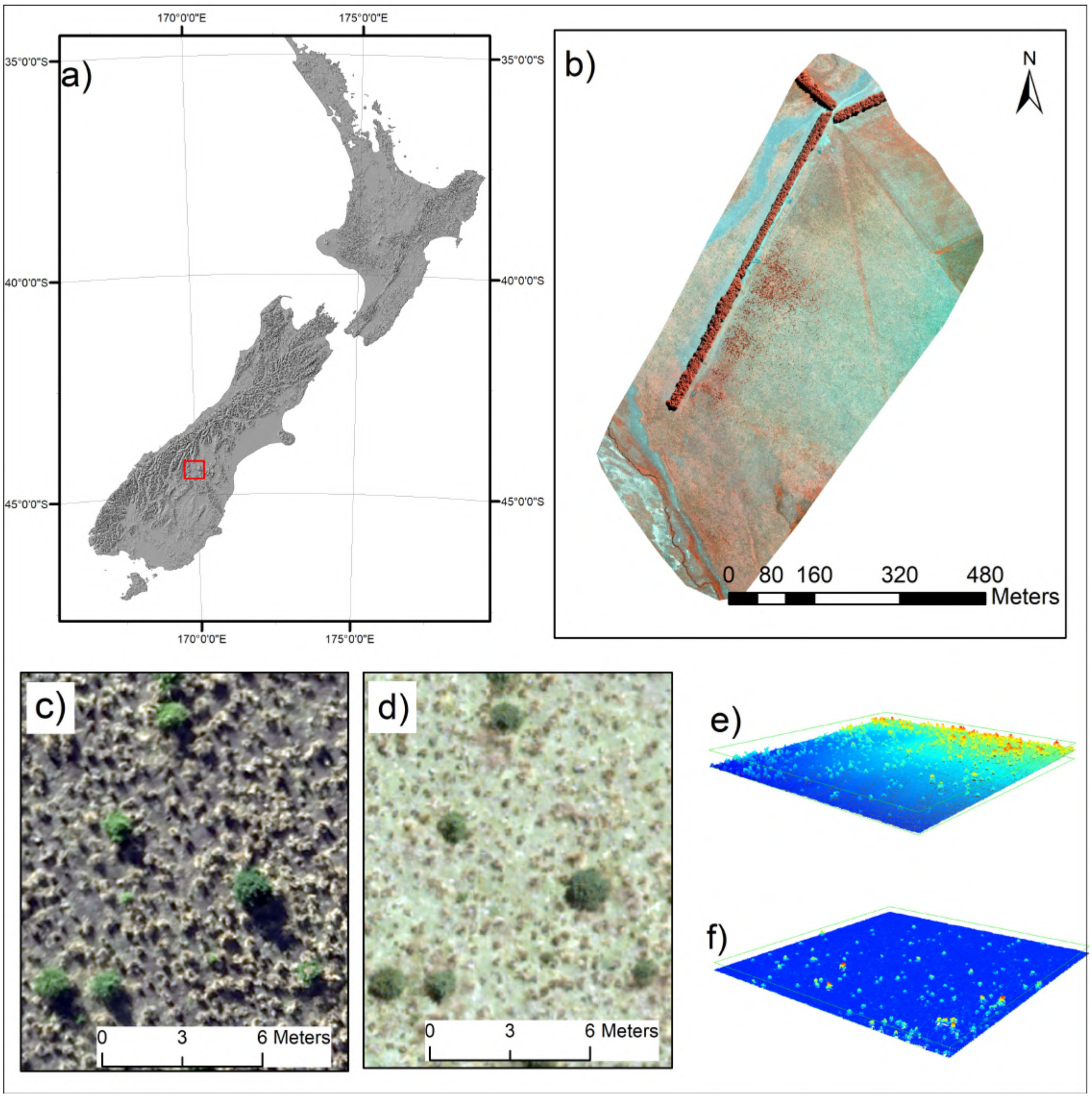

Fig. 4.2 (a) The location of the Mackenzie Basin within New Zealand, outlined in red over a shaded relief map, (b) an overview of the site, (c) a close up of the UAV imagery used in the study, (d) a close up of the piloted aircraft imagery used in the study, (e) a part of the UAV-LS point cloud, and (f) a part of the ALS point cloud collected from the piloted aircraft

4.4.2 Field data

Field data were collected at the study site during an extended field campaign between 15th November 2017 and 10th December 2018. The field campaign was interrupted several times by adverse weather events. The objective of the field survey was to provide a total census of a first order invasion event from a *P. sylvestris* and *P. ponderosa* shelter belt in an open grassland environment. Aerial imagery was used to manually identify the approximate spread fan of the invasion front. This was used to define the boundary for an on-ground comprehensive search of the study area. Excluding the shelter belt all exotic conifers in the area of interest were identified down to a minimum tree height of 0.05 m. The location of each individual was recorded using a Trimble Geo 7X GNSS receiver. At least 100 epochs were recorded for each individual and points were then post processed using a local base station network maintained by Land Information New Zealand (LINZ). In addition to the tree location, detailed information on the properties of each tree were measured. Total tree height was measured using a height pole and crown width was estimated based on two perpendicular tape measurements including the widest point of the crown. In addition to the species, coning (present/absent), and health status (alive/dead) of all trees were recorded. The age of a subset of trees was estimated using the number of branch whorls and the ground cover (bare ground/ tussock/ exotic grass cover) in which younger trees have established (< 1 m ht) was recorded. This field data collection was used to provide ground truth data suitable for developing and validating methods for tree detection of all exotic conifers in the area of interest based on the remotely sensed data available.

4.4.3 Remotely sensed data

Remotely sensed data were collected from the study site using both UAV and piloted platforms. Wall to wall coverage of point clouds derived from laser scanning and orthomoasics of multispectral imagery was acquired from both platforms for the study area.

Piloted aircraft data

Both imagery and ALS data were collected simultaneously on 29th January 2018. Imagery was collected using a Leica RCD30 camera with an 80 mm lens (Field of view 60°) and laser scanning was carried out using a Leica ALS60 scanning system. Data were collected from onboard a Remi Cessna 337 Skymaster across the study site at a flying height of 800 m above ground level. The cruise speed was 120 knots and terrain following was undertaken manually by the pilot. The resultant imagery had a ground sampling distance (GSD) of 4 cm. The 80 MP medium format camera used provided high-resolution four band multispectral imagery with radiance recorded in the blue (450–485 nm), green (500–565 nm), red (625–680 nm), and near-infrared (780 - 880 nm) bands. The laser scanning system was capable of recording up to 5 returns per pulse. Data were collected with a pulse repetition frequency of 120 kHz and a mean swath overlap of 45 % which resulted in a point cloud dataset with a mean point density of 8.28 pts/m^2 (standard deviation = 1.81 pts/m^2) and a mean ground spacing of 0.35 m (Table 4.2). A series of ground control points were established by the provider and used to orthorectify both the aerial imagery and the point cloud data. This resulted in a mean reported accuracy of 0.1 m in both the horizontal and the vertical dimensions with a 90 % confidence interval.

Initial point cloud processing was carried out using the Terrasolid software (Terrasolid Oy, Espoo, Finland). This included tiling, classification of noise points, and ground classification. Subsequent processing was carried out in the LAStools software suite and the lidR package (Roussel and Auty, 2018) within the R statistical software package (R Core Team, 2018).

UAV data

UAV laser scanning data were acquired on the 6th May 2018 using a Velodyne HDL-32E (Velodyne, San Jose, USA) scanner embedded in a RouteScene 'LidarPod' laser scanning system (Mapix Technologies Ltd, Edinburgh, UK). The laser scanner was mounted on a DJI Matrice 600 piloted octocopter platform (DJI Ltd., Shenzen, China), in total 9 flights were required to cover the entire study area. The Velodyne HDL-32E laser scanner has a rotating array of 32 lasers, providing a maximum potential 'scan angle' of 180 degrees from the Routescene system. Only the inner lasers are equiangular and returns acquired with a high off-nadir angle can induce substantial artefacts and noise in the point cloud data when acquired from a UAV. To minimise these effects, only data from the inner-most lasers (+/- 8 degrees off nadir) were retained and a sector reduction filter was applied to limit the effective scan angle to +/-25 degrees. Flight line matching, ground classification, noise removal and the identification of overlap points were carried out in Terrasolid. Subsequently, points classified as overlap were removed to ensure a more even density over the entire study area. A flying altitude of approximately 60 m above the local terrain and a flight speed of 6 meters per second was used. The flight plan ensured that there was significant side overlap to remove the possibility of data voids. All flight manoeuvres and altitude adjustments were made outside of the area of interest to avoid the possibility of flight artefacts in the dataset. The laser scanner was only capable of recording a single return and produced a pulse density of 121 pls/m^2 and a mean ground pulse spacing of 0.09 m (Table 4.2).

Multispectral imagery was acquired on the 9th May 2018 from the same UAV in a separate campaign that included 4 flights. A Sentera Multispectral Double 4K camera (Sentera, Minneapolis, MN, USA) was used for UAV-borne multispectral data collection. This sensor provides imagery in the blue (416-476 nm), green (525-570 nm), red (615-695 nm), red edge (700-740 nm), and near-infrared (830-850 nm). Imagery was captured from an altitude of 80 m agl and flight settings ensured a front and side overlap of 70 and 80 % respectively. The resulting geo-referenced mosaic dataset had a GSD of 2.5 cm.

Table 4.2 Summary of the ALS and UAV-LS datasets used in this analysis.

Platform	Sensor	Point density	Point spacing	Altitude (m)	Returns
UAV	Velodyne HDL32e	121	0.09	60	1
Piloted	Leica ALS60	8.28	0.35	800	5

Data processing

The UAV-LS and ALS datasets were used to generate canopy height models (CHM) covering the study area. Several approaches to CHM generation were trialled and were assessed visually to identify the dataset that contained an accurate representation of the conifer invasion spread with limited data gaps. A CHM was generated from both datasets and was used to produce rasters characterising vegetation height across the study area. The CHM resolution was chosen to reflect the approximate footprint size of each dataset (UAV-LS = 0.1 m, ALS = 0.3 m).

The CHM rasters were co-registered with the multispectral imagery using features that could be manually identified in both datasets using the geo-rectification tool in the ArcGIS software suite (Esri, Redlands, USA). Using the manually identified tie points, rectification was carried out using a first order polynomial (affine) transformation to shift, scale and rotate the raster datasets. The resulting RMSE was 42 and 35 cm for the piloted aircraft and UAV imagery respectively using the 40 link tie points identified independently for each set of rasters. The CHM rasters were resampled to the same resolution as the respective multispectral imagery collected from each platform using the gdalwarp function of the Geospatial Data Abstraction Library (GDAL Development Team, 2016) (GDAL version 2.2.4).

4.4.4 Supervised Classification

Supervised pixel-based classification was used to develop models for detection of invasive conifers. A training dataset was produced through careful digitisation of fifty conifer canopies within a GIS and fifty areas of background vegetation using the multispectral data from each platform. Areas that were very heavily shaded were excluded from the training dataset as this has been shown to improve classification results using UAV imagery (Lopatin et al., 2019). The spatial data were exported from the GIS and loaded into R(R Core Team, 2018) where they were used to extract classified pixels coincident with the selected areas. A training dataset containing 2,057,915 pixels including ground-truth labels indicating conifer/background, spectral data, and CHM elevation data derived from the ALS or UAV-LS. The statistical learning method RF (Breiman, 2001) and LR method using a generalised linear model (GLM) were used. For the RF algorithm, model training was carried out using the Caret package (Wing et al., 2018) using ten-fold cross-validation with three repeats. Classifiers were developed using the R packages ranger (Wright and Ziegler, 2017) for RF, and glm (R Core Team, 2018) for LR. In total, 42 models were developed; these included either spectral data only, spectral data and ALS, or ALS data only and separate models were developed for each platform and model class (RF or LR). The best models of each class for each platform and model type were identified, using the validation statistics calculated for accuracy assessment. These classifiers were used to predict the presence of invasive conifers across the study site.

4.4.5 Accuracy assessment

The predictions from the best performing model of each class identified in Table 4.1 were used for independent validation of model accuracy. An independent validation dataset was generated using stratified random sampling of individual conifers from the field data. Stratification was based on tree height, using classes with 0.25 m increments, with the intention of ensuring that trees of all sizes were included in the validation dataset. It was intended that this would provide insight into the relationship between tree size and classifier performance. Ten individuals were randomly selected from within each stratum. Once identified, the canopies of the invasive conifers in the validation dataset were represented as circular cross-sectional areas - with the diameter of each extracted from the field measured canopy widths. The cross-sectional canopy areas were used to extract pixels from the classification results from the selected models that were coincident with the field measured tree canopies. The mode of the classified pixels within a field measured tree canopy was used to define the overall classification value for a subject tree and statistics were calculated at the tree level. The sampling process was iterated five times to allow the sample to stabilise and reduce the possibility of sample artefacts affecting the interpretation of the results. The independent validation dataset was completed by randomly selecting 800 m^2 square areas of the surrounding land that the field data and imagery indicated were free from invasive conifers.

Accuracy statistics were calculated and used during both the model selection and independent validation. The accuracy of the supervised classification model was assessed through a repeated cross-validation of the training dataset with five folds and ten repeats. Simple accuracy, Cohen's Kappa statistics (Cohen, 1960), area under the receiver operator curve (AUC), and F measure based on the cross-validation were calculated and used to assess classification accuracy. Similarly, these statistics were also calculated at the individual tree level during the independent validation exercise. Furthermore, the sensitivity and specificity of each classification model was calculated to provide further insight into classifier performance. Sensitivity was calculated as the count of true positive classifications divided by the sum of true positives and false negatives. Specificity was calculated as the count of true negatives divided by the sum of true negatives and false positives (Wing et al., 2018).

4.5 Results

4.5.1 Field data

In total 17,514 invasive conifers were identified and measured in the study site during the field campaign. Of this sample, 99 % were either *P. sylvestris* (60 %) or *P. ponderosa* (39 %), these being the two species that comprise the shelterbelt in the study area. A small minority (3.55 %) of the trees were observed to be dead at the time of assessment and these were removed from the subsequent independent validation. The field data showed that the *P. sylvestris* trees within the study area were markedly taller and had larger crowns than the *P. ponderosa* (Table 4.3). Following differential correction, the mean reported precision of the field recorded tree locations was 0.08 m. This level of accuracy is considerably smaller than the crown width of the majority of the subject trees and should not significantly affect the results reported here. Plotting the tree locations showed that the two species were not uniformly intermingled but exhibited species clustering probably associated with the availability of seed source, timing of seed release, and local soil and terrain conditions. Only the *P. sylvestris* was found to be coning in the field dataset (Figure 4.3 b). In total, 657 trees were found to be coning. These trees had an average height of 2.43 m and an average crown diameter of 1.58 m. Notably, the smallest tree found to be coning was only 0.84 m tall (crown diameter of 0.37 m) (Figure 4.3). However, in total, only 5 coning trees (0.07 %) were found to be under 1 m tall.

In addition to the spatial distribution and species composition, the size of the trees and the density of the invasion are also of critical importance. The interaction of

Table 4.3 Summary of the field data collected and used in the independent validation dataset. Values in brackets show the range of the measured tree heights and crown widths.

Species	n	Mean height (cm)	Mean crown width (cm)
P. ponderosa	6,621	40.90 (2-369)	46.59 (1-228)
P. sylvestris	10,032	95.76 (1-476)	102.60 (1-325)

density with tree size affects both the difficulty of detection and the strategy that might be deployed for control and eradication. Based on the field dataset the density of invasive conifers across the study site was calculated (Figure 4.3 a). This analysis revealed that the density of invasive conifers was highest closest to the shelter belt and decreased further away from where only small groups or individuals were present.

4.5.2 Training Data

Two separate datasets were produced for training the supervised classifiers from the remotely sensed data. Graphical analysis of the training datasets provided insight into their properties (Figure 4.4). This analysis showed that there were significant differences between datasets acquired from the UAV and piloted aircraft. It was particularly evident that the tussock areas in the piloted aircraft training data were considerably brighter than their equivalent areas in the UAV training dataset. This is likely due to differences between sensors and variation in the atmospheric and solar conditions in between the two acquisitions. As a result of this, the invasive conifer pixels were considerably more distinct from their surroundings in the piloted aircraft data than in the UAV imagery data in terms of the spectral bands available. However, it is clear from Figure 4.4 that there was a substantial difference in the values in the red edge band between areas containing invasive conifers and those that did not.

For both datasets, the structural properties of the invasive conifers varied greatly from their surroundings as the elevation of returns originating in the invasive conifers

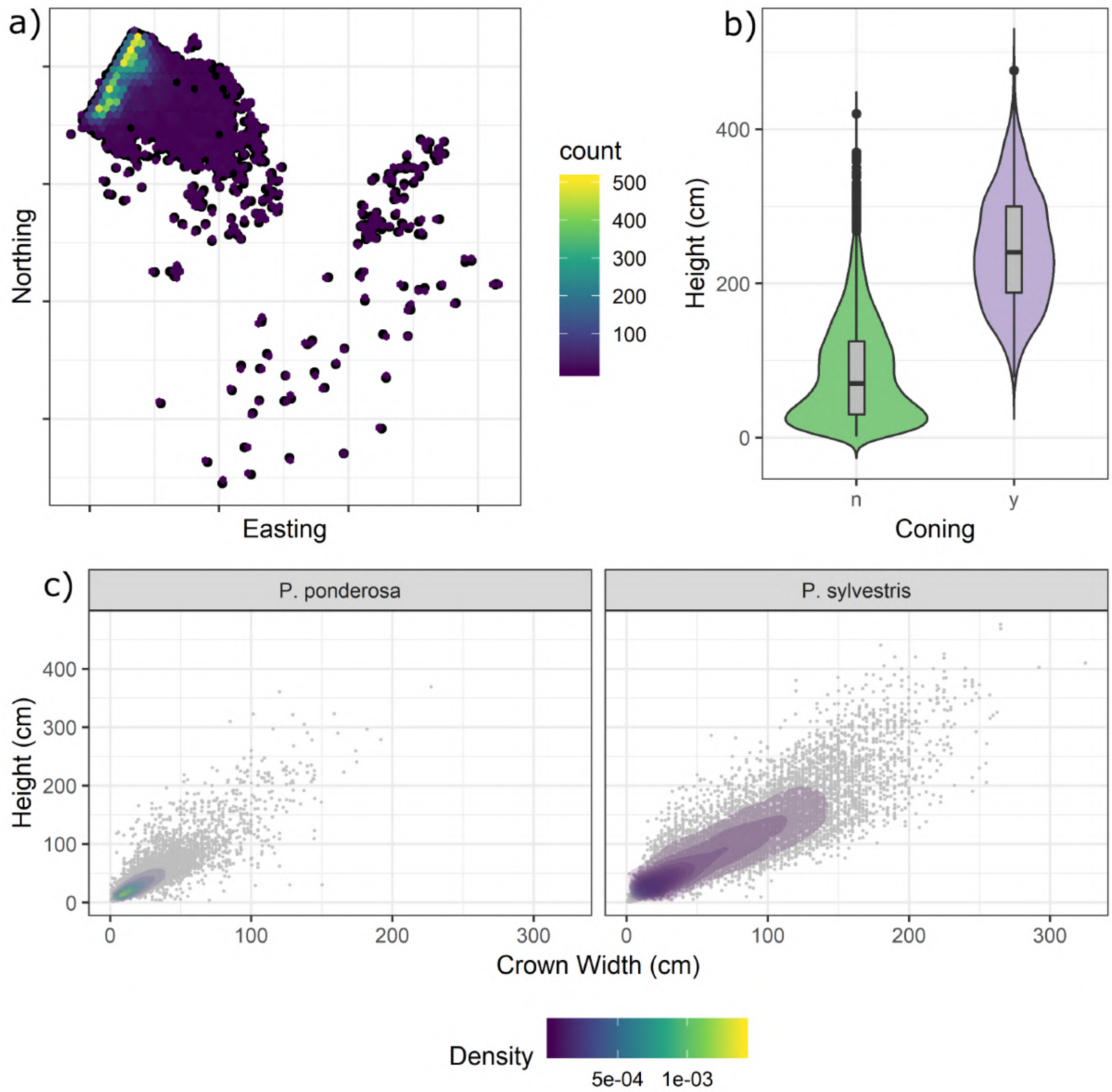

Fig. 4.3 (a) A hexplot showing the spatial distribution and density of invasive conifers in the field dataset, (b) a violin and box plot showing the height distribution of non-coning (n) and coning (y) trees in the field dataset, and (c) the relationship between height and crown width for *P. ponderosa* and *P. sylvestris*.

was usually considerably greater than zero (Figure 4.4). The median and upper quartile of the elevation of returns from invasive conifers were very similar in datasets from both platforms. The lower quartile of the elevation distribution was considerably lower for the piloted aircraft dataset than for the UAV data.

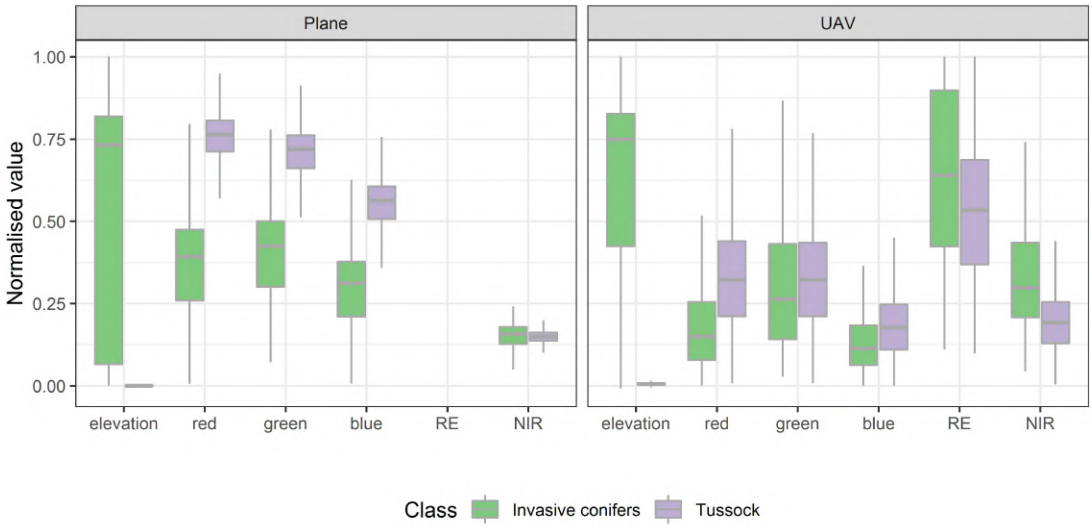

Fig. 4.4 Box and whisker plots of the spectral and structural properties of the training dataset for the piloted aircraft (Plane) and UAV datasets.

4.5.3 Model development

The classification accuracy results extracted from the cross-validation process during model development and model selection are shown in Table 4.4 and Figure 4.5. Models developed using ALS and all spectral data (models 1 and 2), all available spectral data (model 4 and 5), or only ALS (model 3) were exceptionally accurate and had kappa values greater than 0.96 for all four combinations of classifier and platform (Figure 4.5). Similarly, there was very little difference between the classifiers and platform using models with four combinations of spectral bands and these two models (models 4, 5) had very high kappa values (> 0.996) that were very similar to that of the first three models. The models developed with red, green, and blue bands (model 6) were very accurate but the classification accuracy was slightly higher for these models using data derived from the UAV (mean kappa = 0.990) than the data from the piloted aircraft (mean kappa = 0.942).

Using data from the piloted aircraft, the accuracy of the models that used only a single spectral band (models 7 - 11) were very similar between the two classifiers

(Fig. 6). Mean kappa values for these models were respectively, 0.628, 0.617 and 0.406 for models with red, green, and blue bands. For both classifiers, the model with the near-infrared band was the least accurate, but classification accuracy for this model was higher for the RF model (kappa = 0.366) than for the model created using LR (kappa = 0.202). The red edge band was only available using UAV-borne sensor and was more accurate (kappa = 0.732) for the LR than for the RF model (kappa = 0.272).

In contrast to the data from the piloted aircraft, classification accuracy for single band models developed from the UAV were, with the exception of the model with the near infra-red band, markedly lower (Figure 4.5). LR generally outperformed RF with these single band models (Figure 4.5). Kappa values for this classifier were respectively 0.637, 0.794, 0.403 and 0.202 for models 6 - 10, which included the single respective bands of red, green, blue, and NIR bands.

Based on these results, the best performing models for each class (spectral + ALS, spectral, and ALS) were identified and used in subsequent independent validation of classifier performance and mapping of invasive exotic conifers across the study site. The best performing models of the spectral + ALS class and the spectral class contained all available spectral predictors (R,G,B,NIR for the piloted aircraft and R,G,B, NIR, and red edge for the UAV).

4.5.4 Independent validation

Rasters detailing the pixel-wise predictions from the best performing model for each model type were generated for the study area (Table 4.4). Only the best performing models of each class were used for the independent validation (Table 4.4). The independent validation showed that overall the three best performing models used the UAV data for classification. The best performing model was a LR model using all available spectral predictors (kappa = 0.709), followed by a RF model using the

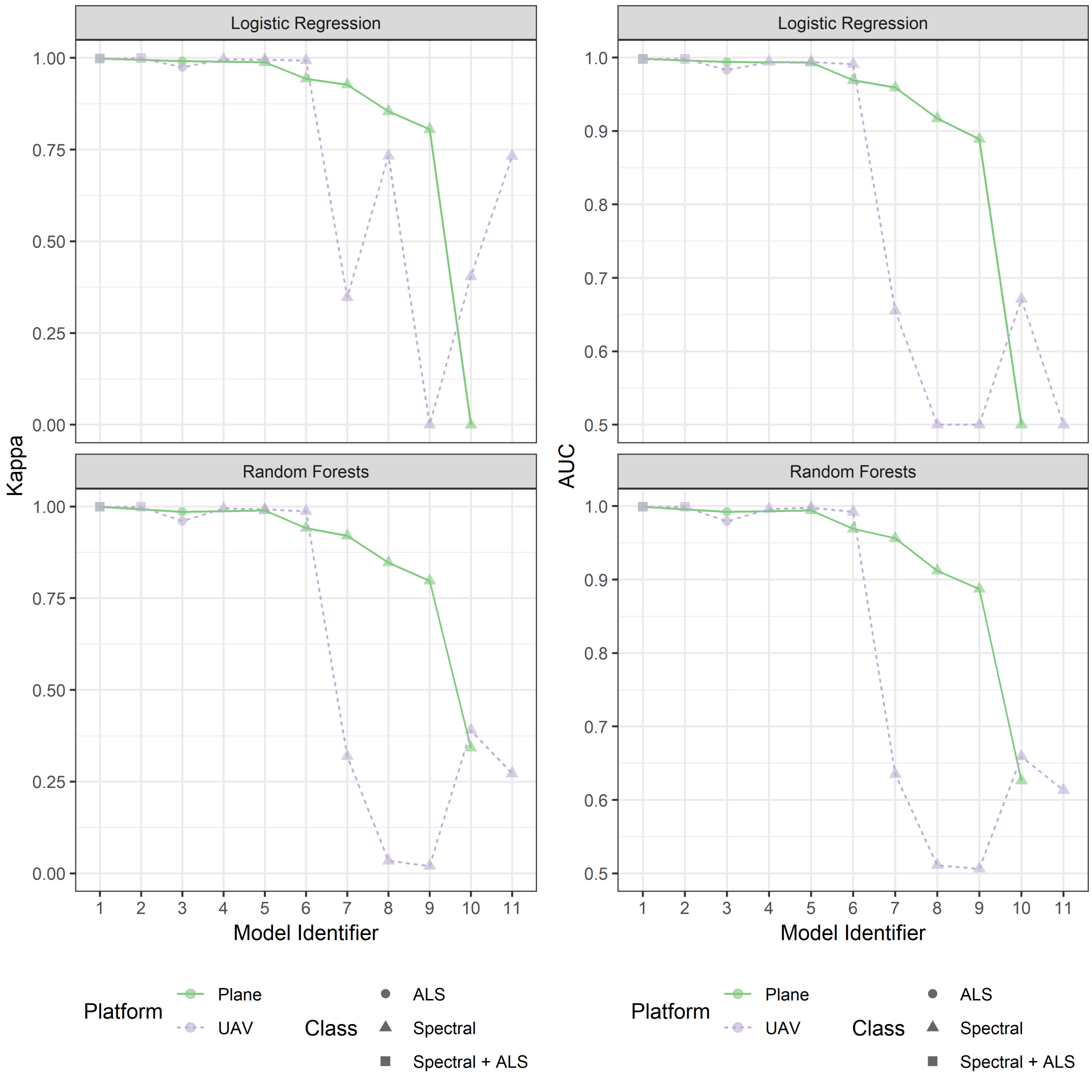

Fig. 4.5 Kappa values extracted from the cross-validation results during model development. Each datum represents the kappa value from cross-validation for a single model. The model identifiers as shown in Table 4.1 are are shown along the X axis and shape of each datum represents the class of model represented. Note that models 2 and 11 could only be developed using UAV data as these included the red edge band.

same spectral predictors (kappa = 0.633), and the RF model using both spectral and UAV-LS predictors (kappa = 0.623). The worst performing models overall were spectral class models developed using the data from the piloted aircraft (RF kappa = 0.478, LR kappa = 0.465) followed by the models produced using the UAV-LS data. By contrast, the models developed using ALS data collected from a piloted aircraft were the best performing models produced using data from this platform. The specificity for all classifiers was higher than the sensitivity. This is evidence that there were very few false negatives in the independent validation dataset but that a significant number of trees within the validation dataset were incorrectly classified (false negatives).

Table 4.4 Summary of the independent validation of model predictions. Model identifiers (Model ID) are as specified in Table 4.1

Model ID	Platform	Class	Classifier	Kappa	Sensitivity	Specificity
5	piloted aircraft	Spectral	RF	0.4646	0.739	0.906
1	piloted aircraft	Spectral+ALS	RF	0.6023	0.802	0.994
3	piloted aircraft	ALS	RF	0.6086	0.803	1
5	piloted aircraft	Spectral	LR	0.4777	0.749	0.906
1	piloted aircraft	Spectral+ALS	LR	0.569	0.781	0.988
3	piloted aircraft	ALS	LR	0.6091	0.804	1
4	UAV	Spectral	RF	0.633	0.819	1
2	UAV	Spectral+UAV-LS	RF	0.6225	0.815	1
3	UAV	UAV-LS	RF	0.5044	0.778	1
4	UAV	Spectral	LR	0.7089	0.865	1
2	UAV	Spectral+UAV-LS	LR	0.6073	0.802	1
3	UAV	UAV-LS	LR	0.4898	0.716	1

Sampling the field dataset as described above provided insight into the relationship between tree size and classification accuracy. This is important to define whether trees can be identified with a high degree of accuracy prior to the onset of coning in this environment. Plotting the agreement between observed and predicted values for the validation dataset (Figure 4.6) revealed that the pattern of detection accuracy was similar for both aerial platforms examined. The accuracy of classifiers from both platforms was low for the smallest trees studied (< 0.25 m) with agreement between observed and predicted below 20%. As tree height increased, the agreement increased rapidly with both platforms approaching 90% agreement for trees 1 m tall. Above this height threshold, detection accuracy reached a 100% agreement between observed and predicted values for the remainder of the validation data. The gradient of the increase in agreement in Figure 4.6 provides insight into the relative performance of models with different sets of predictors. For classifiers based on data collected from the piloted aircraft there was very little difference in the validation curves for the two classifiers examined, indicating that the specificity of these models was similar within a tree size class. By contrast, there was some differentiation in detection accuracy for the different models developed from the UAV data. The classifier developed using only UAV laser scanning had the worst performance and did not reach 100 % agreement between observed and predicted until trees with a height of 2 m were used for validation. The models developed with the UAV spectral data showed a steeper validation curve and approached almost perfect agreement when the trees in the validation dataset were 1 m tall.

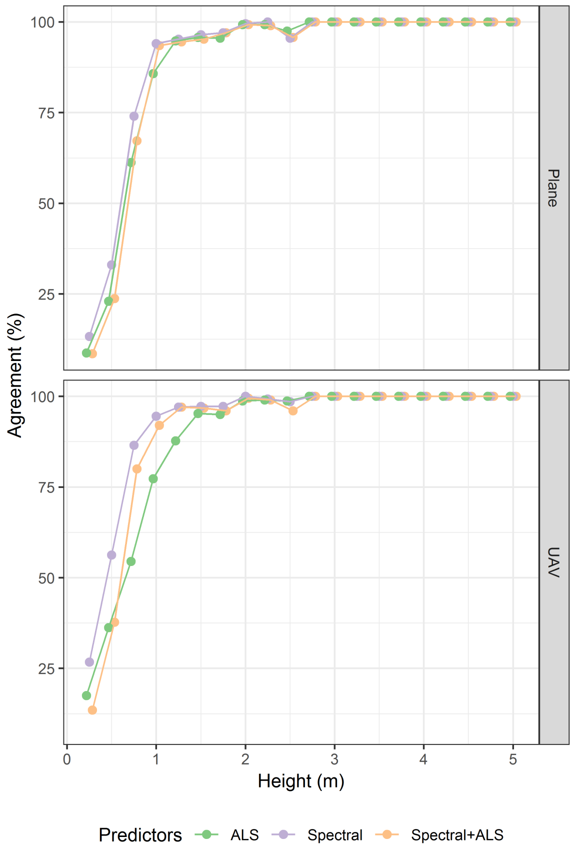

Fig. 4.6 Agreement values for the independent validation dataset for trees within each height class. Each datum shows the mean of the agreement value for both the combined RF and LR models. The UAV and piloted aircraft (plane) data are shown in different panels.

4.6 Discussions

The results of this study clearly show that remotely sensed data collected from both a piloted aircraft and a UAV platform can accurately detect invasive exotic conifers in a study site that was dominated by grassland and small shrub vegetation. The classification accuracy achieved in this study was greater than that reported in previous work aimed at detecting invasive conifers in New Zealand using combinations of ALS and multispectral data (Dash et al., 2017a) or conventional airborne imagery (Sprague et al., 2019). This result was expected as the vegetation and terrain structure in this study were less complex than in the previous work, and spatial resolution of the remotely sensed datasets was higher (Dash et al., 2017a). In contrast to a previous invasive conifer detection study in a similar environment using conventional airborne imagery (Sprague et al., 2019) we were able to identify much smaller trees including the vast majority of trees that had begun coning. This result is significant for managers seeking to eliminate infestations before they reach maturity and become seed sources and suggests that data with higher spectral and spatial resolution is important for this purpose.

The classification accuracy achieved in this study was slightly higher than that reported in comparable supervised image classification approaches. For example, research from South Africa using UAV imagery for invasive plant detection in a semi-arid environment with relatively simple vegetation structure (Mafanya et al., 2017) reported kappa values of 0.8305 and 0.8088 using two different supervised classifiers. However, a conventional consumer grade RGB camera was used in this study and it is possible that the improved classification accuracy we obtained was due to the use of a narrow band multispectral sensor. In more complex environments in Northern Portugal, UAV data has been found to yield lower kappa values (0.51) although these results may not be compared directly because the target plant was not flowering in this study and the imagery used was of a coarser resolution (Alvarez-Taboada et al., 2017).

Our results provide further evidence for the capability of combining multispectral imagery with ALS for detection of exotic conifers in concordance with previous studies (Dash et al., 2017a; Hauglin and Ørka, 2016). We found that combining these two data sources led to the development of models with the highest classification accuracy. However, the magnitude of the accuracy increase associated with the inclusion of ALS was not as great as in previous work (Dash et al., 2017a). This is probably due to the ease of separating the target trees from the surrounding vegetation based on spectral properties in the study environment. This finding would likely be different in a site with greater vegetation height and more complex composition where the fusion of structural (ALS or UAV-LS) and spectral data would be critical. In more complex settings alternative approaches based on object based image analysis or deep learning may be necessary to achieve the required accuracy levels.

This study has shown for the first time that UAV data can be used for highly accurate detection of the early stages of exotic conifer invasions that are characterised by very scattered individuals of smaller statue. This includes very small trees that may not yet have begun coning and provides an operational tool that supports the early and effective control of invasions before new seed dispersal can occur. Our results showed that only 0.07 % of coning trees were shorter than the height threshold (1 m) where we could confidently detect invasive conifers at the cusp of spreading further with a very high degree of accuracy. These results offer the first development of methods for early detection of conifer invasions as there was previously no research into this topic in the existing literature (Juanes, 2018).

The field dataset collected in this study represents the most detailed "ground truth" dataset of its type to the best of our knowledge. This was the result of a significant amount of data collection effort by the field team. While detailed datasets can be collected for scientific purposes, such ground assessments would not be feasible for operational purposes including control and management planning. These applications require quantitative information like coning state, species, tree density etc. Even simplified sampling of invasions is often seen as too costly and remotely sensed data and its analysis can provide such vital information more efficiently for operational tree invasion management across larger landscapes. The magnitude of this work effort shows the importance of developing suitable remote sensing methods for invasive conifer detection and monitoring. Remotely sensed data will be a vital tool for those responsible for control of invasive conifers and monitoring the efficacy of control efforts. These methods can potentially provide accurate information over larger areas using only limited financial resources. The comparison of data collected with different properties and different platforms in this study will also assist land managers with data collection options. The choice of platform and sensor used in practice will be influenced by the properties of the area of interest, the size of area for which information is required, and the budget for data collection. However, our results show that data collected from both UAV and piloted aircraft provide viable and accurate methods for invasive conifer detection.

To the best of our knowledge this is the first study that directly compares UAV and piloted aircraft data for invasive conifer detection with the intention of identifying trees before the onset of coning. Differences in the properties of the training datasets for each platform were observed. The lower quartile of the elevation distribution extracted from the UAV-LS data (Figure 4.4) was considerably lower for the piloted aircraft dataset than for the UAV data. This may be the result of larger footprint and the resulting lower CHM resolution of the piloted aircraft data compared to the UAV-LS dataset. Alternatively, this could be caused by the multiple, rather than single, return capability of the piloted aircraft scanner resulting in a greater penetration and characterisation of smaller trees and areas where the invasive conifer canopy was dense. Alternatively, the positional accuracy of the UAV-LS data cannot be ruled out as a source of this result despite the rigorous approach taken to minimise this error. Despite these differences data from both the UAV and the piloted aircraft platforms resulted in high classification accuracy in this study.

Separate training datasets were developed for each data collection platform based on the remote sensing data. This was necessary because of the differences between the datasets due to the spectral properties, spatial resolution, and differences in shadow levels due to the time of year when the imagery was acquired. The properties of the dataset showed better spectral separation between the invasive conifers and the surrounding tussock in the piloted aircraft data. This may be the result of the greater sophistication of the piloted aircraft mounted camera and the generally better illumination of the scene in the aeroplane imagery as it was collected in summer. Both data sources exhibited excellent differentiation in the elevations extracted from the ALS data. This is likely the result of the simplistic nature of the study site where the majority of vegetation with a height significantly greater than zero were invasive conifers. The misclassification of objects below 1 m for ALS alone was due to tall tussocks and shrubs that were occasionally present at the site due to the land use history and effects of grazing on the surrounding vegetation.

Two different image classification approaches were successfully developed and compared for both data sources. The RF algorithm was carefully tuned using an exhaustive search, which requires significant additional computing time. The simpler LR classifier does not require tuning in the same manner and so is substantially less computationally demanding. The accuracy of both classifiers was very high and were comparable. The RF algorithm performed slightly better than LR for the more complex models including more predictors. However, for the simpler models containing fewer predictors the LR outperformed RF algorithm. As a result, in this study area we would recommend the use of the simpler algorithm as gains associated with the use of the machine learning were absent or minimal and do not justify the additional complexity of using a model of this type. However, this may not be the case in more complex environments where the ability of the machine learning algorithm to better characterise complex and non-linear patterns in the fitting data may be more valuable. Other research into image classification for invasive plant detection has used "one class" algorithms with the results suggesting a high levels of accuracy (Lopatin et al., 2019; Piiroinen et al., 2018). These approaches have the advantage of only requiring identification of a single positive class during algorithm training. This means that errors associated with incorrectly specified training datasets would be reduced and the requirement for field data collection is lessened.

The performance of models with different candidate predictor variables provided insight into their capacity for invasive conifer detection. A particularly noteworthy observation was that there was little improvement in classification accuracy when ALS or UAV-LS data was combined with multispectral imagery. This result is likely the consequence of the simplistic vegetation structure and composition in the study site. The dominant short tussock grasses and exotic grasses have very different spectral properties to those of the invasive conifers, this is particularly evident during the summer months when the grasses are commonly brown. This finding indicates that significant expense can be avoided by only collecting one type of remote sensing data. However, the ALS and multispectral data collected from a piloted aircraft for this study were collected during the same mission so there is limited additional cost for the acquisition and no negative aspects as long as the acquisition settings are optimised for the most important dataset. Currently UAVs of the type used in this study are not capable of carrying two miniaturised sensors to collect data over a large area. Developments in UAV technology such as large, fixed-wing UAVs with alternative power sources will likely make this feasible in the near future. It should also be noted that there is an additional cost associated with data storage and processing when additional datasets are collected.

4.7 Conclusions

In this study we have evaluated the capability of pixel-based classification methods to identify invasive conifers in a vulnerable grassland environment. We found that high-resolution data collected using both UAV and piloted aircraft was valuable for this task. Critically, the vast majority of seed-producing individuals were accurately identified despite the fact that they were very small. This was in part due to the very high spatial resolution of the data acquired. Both data sources and both classification approaches examined provided highly accurate classification results.

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Chapter 5

Transferability of UAV-based models for invasive conifer mapping across a site complexity gradient

5.1 Preamble

Emerging UAV technology is clearly an important new data source for invasive plant detection and monitoring. In this chapter a study is presented where the portability of UAV-based models of invasive conifer distributions was tested. This carefully designed and implemented experiment allowed the effects of transferring models to different areas within the same site and transferring models to sites with different terrain and background vegetation characteristics to be studied. The experimental design incorporated a range of sites that represent the dominant vulnerable habitat types in New Zealand. The sites also comprise a gradient of site complexities and so allow the impact of donor and recipient site complexity on model transferability to be investigated. This study was developed to address RQ2 in this thesis and has been prepared as a manuscript for publication that is currently undergoing peer-review.

Dash, J.P., Paul, T.S.H, Morgenroth, J., Watt, S. (2020) Transferability of UAV based models for invasive conifer mapping within and between sites across a site complexity gradient. In review.

5.2 Abstract

Conifers have been widely planted outside their natural ranges to provide ecosystem services including wood and fibre provision, erosion mitigation, and carbon sequestration. In some environments these trees have become invasive and threaten indigenous ecosystems. To mitigate damage from invasive exotic conifers significant control efforts are underway in many areas. Spread mitigation requires accurate methods for detection and monitoring of conifer invasions that can operate at a range of scales. In recent years unpiloted aerial vehicle (UAV) data has emerged as a useful tool for invasive conifer detection over medium-sized areas. Conventional modelling requires a reference dataset usually collected from the field or acquired through image interpretation of remotely sensed data. We hypothesised that models developed in one location could be transferred to another location without the collection of additional reference data nor additional model development and tested this through an experiment using UAV-based invasive conifer distribution models. This was tested through a series of experiments where models were transferred from one area of interest (AOI) to another, both within sites with similar background conditions and to other sites with markedly different vegetation composition and terrain characteristics. The study was undertaken in New Zealand and designed to encompass a range of site complexities ranging from flat sites with simple vegetation structure to sites with complex terrain and vegetation structure. We first developed highly accurate models of invasive conifer distributions based on combinations of multispectral imagery collected from a UAV and conventional airborne laser scanning (ALS) data for all areas of interest. We found that these models were

portable within a site without need for additional calibration. We then applied each models to all other areas of interest and found that models were robust to transfer to simpler sites but not to more complex sites. We also found that models based on spectral data were more robust to transfer to more complex sites than those used for model development that included ALS data. Based on our results we concluded that UAV-based models for invasive conifer detection can be transferred to other sites with similar, or simpler, characteristics than the site used for model development. This could lead to significant efficiencies as models can potentially be reused without the collection of additional reference data and model development. However, applying models to more complex and markedly different environments can result in very inaccurate predictions.

5.3 Introduction

Humans have translocated many plant species outside of their natural ranges to support economic activities, provide ecosystem services in support of expanding or migratory populations, or by accident (Kueffer, 2017; Meyerson and Mooney, 2007). These plants are referred to as alien plants (Richardson et al., 2000) and a subset of these can reproduce freely in their new environment and regularly invade, and out-compete indigenous vegetation (Simberloff et al., 2013; Vaz et al., 2018b). These characteristics of invasive alien plants (IAP) are recognised as a major driver of human-induced environmental change (Hulme, 2003). This is often exacerbated due to their different evolutionary history compared to the recipient biotic community (Dash et al., 2019b; Kueffer, 2017; Saul and Jeschke, 2015) resulting in traits that afford a competitive advantage (Richardson et al., 2000). These traits may include rapid growth, prolific early seed production, and tolerance of poor site conditions, which are frequently advantageous to humans offering substantial ecosystem service provision. However, without careful management, IAP can cause dramatic changes in ecosystem function and structure (Pejchar and Mooney, 2009) and can have economic impacts by adversely affecting agricultural land (Velarde et al., 2015), rural infrastructure, and may reduce natural capital (van Wilgen et al., 2001).

Both effective management of IAP and research into invasion processes require detailed spatial data on their location and spread (Courchamp et al., 2017; Kattenborn et al., 2019b). These requirements must be supported by appropriate detection and monitoring procedures (Richardson and Rejmanek, 2011) and traditional methods including observer-based surveys are inadequate, expensive, and difficult over mountainous or challenging terrain (Dash et al., 2017a). This is particularly problematic as high-altitude areas are amongst the ecosystems most threatened by IAPs and their vulnerability to damage is exacerbated by the changing climate (Dainese et al., 2017).

To facilitate better characterisation of IAP distribution and spread, a significant body of research has been undertaken into the development of remotely sensed data in many ecosystems (Hall and Asner, 2007; Hestir et al., 2008; Mureriwa et al., 2015) and across several terrain types (Dash et al., 2017a, 2019b,c). This research has comprised studies using multiple platforms and sensor configurations and has been summarised in several detailed reviews on the topic (Dash et al., 2019b; Huang and Asner, 2009; Vaz et al., 2018a). Detection efficacy has been found to vary according to site specific spectral and structural traits of the target IAP in relation to the host habitat (Niphadkar et al., 2017).

Sensor systems are typically characterised through their spectral, spatial, and temporal resolution and matching these characteristics to the intended use is critical to ensuring accurate results at an appropriate scale (Dash et al., 2017a). Furthermore, the areal coverage of remotely sensed data varies considerably by platform type and there is typically a trade-off between the extent of the area and the spatial resolution of data available. Many studies have employed satellite data to track invasions across large areas and these remain the only viable source of data where information is required at regional or national scales (Khare et al., 2017; Lantz and Wang, 2013; Ng et al., 2016). For targeted detection of small or difficult to detect targets high-resolution data sources such as unpiloted aerial vehicles (UAVs) have also been deployed for detection in several environments (Dash et al., 2017a, 2019c; Dronova et al., 2017; Lopatin et al., 2019).

Improved detection has been demonstrated through combining data sources as this allows the model to access the favourable properties of each constituent dataset. This may include the combination of datasets to enhance the accuracy of detection (Dash et al., 2017a) or may use the different areal coverage of different types of remotely sensed data to provide information at a suitable scale. For example, a recent study based in Chile (Lopatin et al., 2019) used UAV imagery as reference data for the classification of satellite imagery to detect invasive species in the absence of conventional field data with considerable success. This is an innovative and highly useful methodology particularly in remote or mountainous areas where the collection of field data is expensive and can be dangerous or near impossible.

In addition to the challenges of field data collection mountainous terrain also presents unique challenges for the processing of remotely sensed data (Weiss and Walsh, 2009) that might affect the accuracy of IAP detection. Mountainous areas typically include steep and complex terrain that require additional corrections to reduce spectral biases and aspect dependent illumination differences, topographic shading, and geometric distortion (Weiss and Walsh, 2009). Illumination differences can cause particular challenges for pixel-based classification approaches through aspect related variability in reflectance values. Methods for illumination correction are well established (Meyer et al., 1993) and correction methods based on topographic analysis have also been developed (Colby and Keating, 1998; Riano et al., 2003) although using spectral indices based on band ratios offer a simpler solution to this challenge (Weiss and Walsh, 2009). Shadowing is a significant issue in remote sensing and previous research has indicated that exclusion of shaded areas improves classification accuracy (Lopatin et al., 2019). In mountainous areas topographic shadowing can make many areas extremely difficult to capture in full sunlight, and this issue is exacerbated in winter and in higher latitude areas in both hemispheres. Illumination corrections alleviate this issue in many instances but care must be taken when applying a classification to ensure that shadowing doesn't adversely affect outputs (Weiss and Walsh, 2009). Geometric distortion occurs in mountainous areas because the topographic relief means that some objects are closer to the sensor than others causing problems during geo-rectification. This problem is less persistent in UAV data or data from low-flying aircraft because these platforms typically have terrain following capability. For satellite imagery a digital terrain model can be used in mountainous areas during rectification to warp the images and alleviate geometric distortion (Toutin, 2004).

In New Zealand, exotic conifers have been very widely planted since the early 20th century and a small number of species now form the basis of a vibrant, commercial forestry sector. These forests play an important role in New Zealand's economy and also contribute to erosion prevention, water filtration, social values, and carbon sequestration (Nunez et al., 2017). Unfortunately some historically planted exotic conifer species have become invasive into indigenous and semi-indigenous ecosystems with vegetation invaded by conifers at highly variable densities now estimated to cover approximately 2 million hectares (Anon., 2011) or 7% of the total land area. This includes many areas with significant cultural values and there is a consensus that these incursions must be curtailed. A significant portion of the affected areas include steep, mountainous terrain in the Southern Alps of New Zealand's South Island (Te Waipounamu) and in the mountain ranges and volcanic peaks of the North Island (Te

Ika-a-Māui). These areas include a significant range of vegetation composition and structure with extremely varied terrain extending up to 5,000 m asl but also including large plateau areas dominated by grasslands.

Significant research effort has been expended to customise IAP detection methods for New Zealand conditions. Theses have included approaches that have used satellite imagery, imagery collected from piloted aircraft (Dash et al., 2017a; Sprague et al., 2019), and methods using UAVs for targeted detection of individual trees prior to the onset of seed production (Dash et al., 2019c). Despite the promise of these studies and the practical implementation of many of the results, these studies have to date encompassed relatively homogeneous and simplistic study sites, thereby omitting highly complex or mountainous terrain. In recent years UAV have emerged as useful tools in the monitoring of invasive alien plants (Dash et al., 2019c; Kattenborn et al., 2019b; Lopatin et al., 2019; Perroy et al., 2017). These craft have become a reliable, cost-effective, and flexible method for the collection of high resolution data over moderately sized areas (Heaphy et al., 2017; Vaz et al., 2018a).

Conventional approaches to mapping require a detailed reference dataset that is used to train an algorithm that is subsequently applied to classify the remotely sensed data. This allows observations to be modelled across the entire extent of an area of interest (AOI). Reference data is usually sourced either from field data collection or through human interpretation of imagery. Regardless of the method used collation of a high quality reference dataset is a labour intensive and time consuming process and can introduce significant errors that can be difficult to quantify. This effort and source of error can be reduced by transferring models developed using a reference dataset to another area, provided the reduction in prediction accuracy is not too high. However, for this to be undertaken with confidence quantitative data on the portability of models both within and between sites is required. The error structure is likely to be affected by the properties of both the AOI used for model development (donor) and the AOI to which the model is applied (recipient). To the best of our knowledge no such information is available relating to the portability of UAV-based models for invasive plant distributions. In this study we investigated this using data from five AOI across three study sites with a range of vegetation and terrain characteristics throughout New Zealand. We tested the hypothesis that UAV-based models of invasive conifer distribution could provide accurate prediction results when transferred to AOIs that were not used for model development. In addition to this central hypothesis our study had the following specific objectives.

1. To examine the relative importance of spectral and ALS-based predictors for mapping invasive conifer distributions in several vulnerable environments;

2. To test whether the developed invasive conifer distribution models from a given donor site can provide accurate results when they are transferred to and validated using data from a different AOIs (recipient) within the same site;

3. To test whether invasive conifer distribution models can provide accurate results when they are transferred to new datasets from different sites with varying complexity;

4. To investigate the interaction between the site complexity of both the donor dataset used for model training and the receiver dataset used for model validation.

5.4 Materials and methods

5.4.1 Study sites

This study was conducted across five AOIs each containing UAV imagery and a coincident airborne laser scanning dataset and covering areas containing varying amounts of invasive conifers at a range of densities. The AOIs were spread across three study sites in the Hanmer Forest Park (HFP), Kaweka Forest Park (KFP), and in the vicinity of Lake Pukaki (LP) in New Zealand (Figure 5.1). These study sites represent a range of the environments in New Zealand that are threatened or invaded to various degrees by invasive exotic conifers (Ledgard, 2003). They also constitute a site complexity gradient in terms of both the terrain characteristics and vegetation structure and composition.

The simplest study site is at LP which is flat and has a low diversity and abundance of trees and shrubs. The area is dominated by short tussock grasslands (Weeks et al., 2013) and there are few trees and shrubs excluding the introduced invasive conifers. The site at HFP is variable as it encompasses alpine areas, river terraces, riparian areas, shrub areas with exotic and native species and remnant mountain beech forests (*Fuscospora cliffortiodes* (Hook.f.) Heenan et Smissen). The HFP site has moderate shrub and tree diversity and abundance and includes many non-target objects including rocky outcrops and other features. The KFP site is the most complex site included in this study and is characterised by steep and broken terrain, and very high non-target tree and shrub abundance and diversity. Mountain beech, Manuka (*Leptospermum scoparium* J.R.Forst. & G.Forst.), Kanuka (*Kunzea ericoides* (A.Rich.) Joy Thomps.) and various Coprosma species are common and intermixed with tall tussock (*Chionochloa* sp.) and exotic grasslands (*Agrostis capillaris* L.). A more detailed description of each site is provided below and representative UAV imagery for each site is included in Figure 5.1 to provide context to the vegetation conditions. Remotely sensed data were collected within each site by both piloted aircraft, as part of a larger survey, and from a UAV over targeted AOIs. Within the HFP site, three separate and non-overlapping UAV datasets were collected, while only a single UAV dataset was collected at each of the other two sites.

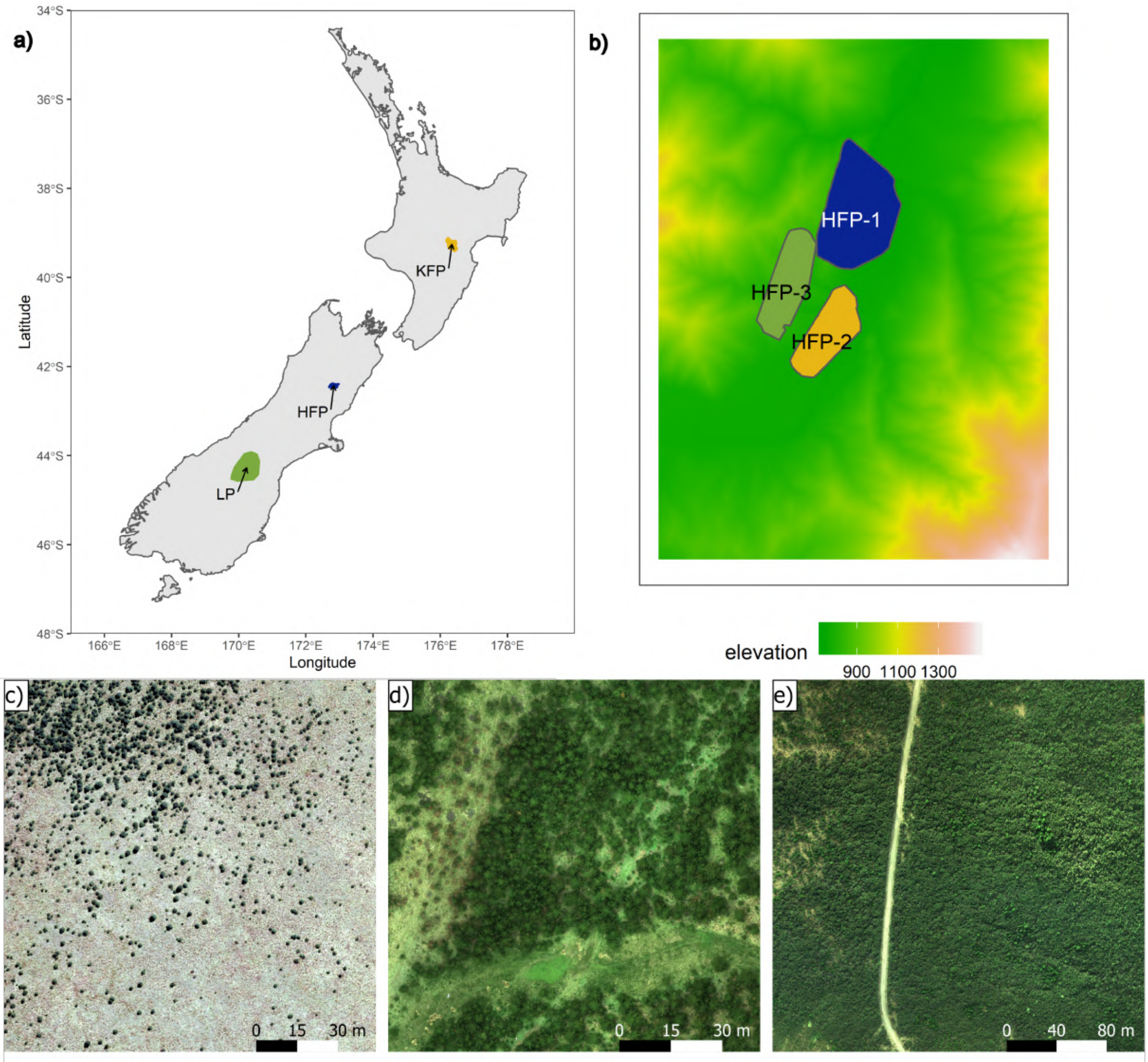

Fig. 5.1 The location of the three study sites (Hanmer Forest Park = HFP, Kaweka Forest Park = KFP, Lake Pukaki = LP) within New Zealand (a). The footprint of the three AOIs covered by UAV data within HFP overlaid onto a terrain model of the area (b). Examples of the UAV imagery collected at (c) LP, (d) HFP, and (e) KFP showing the range in vegetation complexity between the three study sites.

5.4.2 Lake Pukaki Site

The LP study site is located in the Mackenzie Basin, South Canterbury in the South Island of New Zealand and has previously been described in Dash et al. (2019c). Topographically the area was strongly influenced by its glacial history with in-filled and now wide expanding river terraces and glacially-formed rounded hills surrounded by high altitude mountain ranges. The study area is within the Mackenzie Basin which lies between 600-1100 m a.s.l. with higher slopes and hilltops also present near Lake Pukaki. The climate is continental with dry hot summers and cold winters. The area has been dominated by native (and more recently a growing proportion of exotic) grassland species for at least the last 500 years and has been subjected to 200 years of pastoral management of varying intensities. This management combined with frequent burning, overgrazing, and rabbit (*Oryctolagus cuniculus*) outbreaks has resulted in a high level of degradation of the natural short and tall tussock grassland (*Chionochloa* and *Festuca* species) and herb and shrub communities, now dominated by exotic grass species such as *Agrostis capillaris* L. and *Anthoxanthum odoratum* L.

Sources for exotic conifers have been historic plantings of shelter belts and woodlots for soil conservation, shelter, scenic, and recreational purposes across the basin. Some commercial plantings were also established over time to create a timber resource. Exotic conifer species originating from these plantings have now become invasive over thousands of hectares and the initial low densities of scattered trees are now expanding to become grassy woodlands, and even dense forested stands in some areas. The major species that have spread across most of the basin and have been controlled, but not eradicated, include *Pinus contorta* Douglas (*P. contorta*), *Pinus nigra* Arnold (*P. nigra*), *Pinus sylvestris* L. (*P. sylvestris*), *Pinus ponderosa* Douglas (*P.ponderosa*), *Larix decidua* Mill. (*L.decidua*) and *Pseudotsuga menziesii* (Mirb.) Franco (*Ps. menz*).

The core study area used in this site was a 22.4 ha AOI in the immediate vicinity of a shelter belt planted with a mixture of *P. sylvestris*, *P. ponderosa* and a small number of *P.nigra*. The study site is 804 m asl and is located around 11 km west of the township of Tekapo (Latitude = 43° 59'02.30 S, Longitude = 170° 20'22.43 E). This site was selected because it represented a first order invasion event of significantly problematic invasive conifer species within this region. The flat terrain of the study site represents mostly short tussock grassland, the common vegetation type in the lower parts of the Mackenzie Basin. Most common native and exotic grasses are short stature tussock species such as *Festuca novae-zelandiae*, *Poa colensoi* and exotic grasses such as *Agrostis* spp. and *Anthoxanthum odoratum.* Shrubs including *Coprosma petriei* and *Discaria toumatou*, mostly in the prostrate growth form, are also present in low numbers. The herbaceous component of the vegetation is dominated by exotic *hieracium* species.

5.4.3 Hanmer Forest Park

The study site at HFP is located close to the township of Hanmer Springs in northern Canterbury in the South Island of New Zealand. The area is characterised by steep slopes with gullies, rounded mountain tops and flat river terraces. The natural vegetation is a mix of short tussock grasslands on river terraces, shrub, tall tussock grasslands and herb fields on slopes and mountain tops and localised mountain beech forest.

To the south lies Hanmer Plantation Forest which was the result of planting of exotic conifers started as early as 1902. By 1924, Hanmer Plantation Forest covered 2430 ha and the major exotic conifers were *P.nigra*, *P.ponderosa*, European *Larix decidua* and *Pseudotsuga menziesii.* Lodgepole pine (*P.contorta*) was planted in a small area at Percival streams (part of the study area). From these areas the spread of invasive conifers is now present further to the north over the ridge of the Hanmer Range with Mt Isabel (1319 m asl) into the wider valley terraces (800 m asl) of the Clarence and Acheron rivers and the adjacent slopes. *P.contorta* and *P.nigra* are now dominating the infested areas found in these areas. Newer plantings have been established on the south facing slopes of the Hanmer Range primarily using species that are less invasive such as *Pinus radiata* D. Don.

5.4.4 Kaweka Forest Park

The study site is part of the KFP in the western part of Hawkes Bay, in New Zealand's North Island. Topographically the study areas are characterised by steep to medium-steep slopes, ridges and hilltops with elevations ranging from 600 – 1000 m a.s.l. Mean annual max–min temperatures are approximately 5.6–15.3 C and mean annual precipitation is 1279 mm. The natural vegetation of the site is composed of herb fields and snow tussock areas in the highest altitudes of the range. Forest types include New Zealand beeches *Fuscospora cliffortioides* (Hook.f.) Heenan & Smissen and *Fuscospora fusca* (Hook.f.) Heenan & Smissen, native conifers (*Podocarpaceae* Endl.), and native broadleaf species (e.g. *Pittosporum* Banks ex Sol.). In the eastern areas in which the study sites are located, fires and historic grazing have been responsible for a change towards manuka (*Leptospermum scoparium* J.R.Forst. & G.Forst.) and kanuka (*Kunzea ericoides* (A.Rich.) Joy Thomps.) shrublands which are now replacing the natural forests in wider parts of the study area.

Invasive conifers have been introduced into the area by plantings and aerial sowing projects by the New Zealand Forest Service as early as 1959 with the intention of stabilising erosion-prone slopes. The main species used was *Pinus contorta*, but other conifer species and even native tree species were tested for their ability to stop erosion. Some of these earlier experimental plantings still exist and are part of the study site. Due to rising concerns about the increasing spread of invasive conifers, a control programme was started as early as 1981 but this did not sufficiently stop the spread that can now be observed in many areas (mainly the higher ridges), which were once dominated by more open natural vegetation such as tussock and low open shrubs.

5.4.5 Data sets

In total five datasets were assembled and used in this study (Table 5.1). Remotely sensed data were collected across all study sites for the purposes of this study. ALS data were acquired for KFP using a Trimble AX60i laser scanner onboard a fixed-wing aircraft at a height of 700 m. A scan rate of 136 Hz and a pulse repetition rate of 360 kHz were used with a maximum scan angle of 60 degrees. Flight settings ensured a side overlap of 60 % and the scanner recorded up to seven returns from each emitted pulse alongside return intensity data. The resulting dataset had a mean point density of 14.5 points/m^2 with mean ground spacing of 0.26 m for last returns. For HFP and Lake Pukaki laser scanning was carried out using a Leica ALS60 scanning system mounted on board a Remi Cessna 337 Skymaster with data acquired across the study site at a flying height of around 800 m. The laser scanning system was capable of recording up to five returns per pulse. Data were collected with a pulse repetition frequency of 120 kHz and a mean swath overlap of 45 % which resulted in a point cloud dataset with a mean point density of 8.28 pts/m^2 and a mean ground spacing of 0.35 m. In all three study sites the data supplier collected a set of ground control points that were used to minimise errors in the resulting dataset.

UAV-borne multispectral imagery was acquired from a DJI Matrice 600 remotely piloted octocopter platform (DJI Ltd., Shenzen, China) during five separate campaigns. For all AOIs within each site a Sentera Multispectral Double 4K camera (Sentera, Minneapolis, MN, USA) was used for multispectral data collection. This sensor provides imagery in the red (615–695 nm), green (525–570 nm), blue (416–476 nm), red edge (700–740 nm), and near-infrared (830-850 nm) bands. Imagery was captured from an altitude of 80 m agl and flight settings ensured a front and side overlap of 70 and 80 % respectively. The resulting geo-referenced mosaic dataset had a ground surface distance (GSD) of 0.03 m at LP, 0.06 m at HFP, and 0.05 m at KFP.

Table 5.1 Summary of the UAV AOIs in each of the three study areas. This includes an estimate of the percentage area occupied by invasive conifers calculated using the reference dataset described below

Site	**Identifier**	**Area (ha)**	**Dominant spp.**	**Site complexity**	**% cover**
HFP	HFP-1	43.6	*P. contorta*	Moderate	10.2
HFP	HFP-2	20.2	*P. contorta*	Moderate	23.5
HFP	HFP-3	21.3	*P. contorta*	Moderate	47.6
KFP	KFP-1	122.6	*P. contorta*	High	4.4
LP	LP-1	38.1	*P. sylvestris*	Low	5.5

5.4.6 ALS Data processing

Initial data processing for all ALS datasets including flight line matching and noise removal which was carried out by the data supplier using the Terrasolid software suite. Subsequent processing was undertaken using LAStools (https://rapidlasso.com/) and included further noise removal and classification into ground and non-ground returns. Ground returns were triangulated into a digital terrain model (DTM) which was used to normalise the height of returns to the local terrain. Subsequent ALS processing including tree detection were carried out using the LidR package (Roussel and Auty, 2018) in the R statistical computing environment (R Core Team, 2018).

A set of wall-to-wall metrics were calculated across each AOI at a 1 m resolution. The metrics calculated were selected as they describe vegetation height, density, and structure. These included height percentiles ($H_{5,10..95}$), canopy densities ($b_{5,10..95}$), statistics describing the distribution of return height ($H_{kurtosis,\ skew,\ sd}$) and cumulative percentiles as described in detail in Pearse et al. (2017). A similar range of descriptive metrics was also calculated from the uncalibrated laser intensity data. It was thought that intensity metrics might provide data useful for discriminating between plants with different reflective properties.

5.4.7 Spectral Data

Ortho-mosaic creation from the UAV multispectral imagery was undertaken using a commercial software product (Pix4D, Prilly, Switzerland) using a standard photogrammetric workflow. This procedure included image quality checking prior to image matching and the removal of poor-quality images. Location data for georeferencing were provided using a combination of the trajectory from the onboard GNSS device used during the flights and a series of ground control points (GCP) collected throughout the study areas. The location of the GCPs was fixed using a survey grade GNSS with external antennae and differentially corrected post data capture using a set of local base stations maintained by Land information New Zealand (LINZ). Although collection of GCPs can be time consuming we deemed it necessary as absolute positional accuracy of the resulting ortho-mosaics was important to ensure accurate matching to the ALS data collected in a separate campaign.

The UAV-borne multispectral imagery was used to calculate vegetation indices for the study area. Invasive conifers have quite distinct spectral properties that are useful for distinguishing them from other non-target vegetation in New Zealand. Spectral indices were calculated and used because they reduce the dimensionality of the data, stabilise any differences between acquisitions or between areas with differing illumination conditions, and provide useful information on the spectral properties of the vegetation within the area of interest. Given the available spectral bands of the multispectral camera we used two well known and widely used vegetation indices. The normalised difference vegetation index (NDVI) (Rouse et al., 1974) and the red edge normalised difference vegetation index (RENDVI) (Gitelson and Merzlyak, 1994) were calculated using equation 5.1 and equation 5.2, respectively.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{5.1}$$

$$RENDVI = \frac{(RedEdge - Red)}{(RedEdge + Red)} \tag{5.2}$$

5.4.8 Tree detection and reference dataset development

To identify all areas containing invasive conifers within each AOI we used a two-phase semi-automated approach. During the first phase automated tree detection was used to identify candidate objects that might be invasive conifers within each AOI. In the second phase we manually reviewed and adjusted the outputs of phase one to improve the accuracy of the representation of invasive conifers. This data set was critical as it was used both for model training and model validation. Following initial tests with object-based image analysis (OBIA) we found that tree detection based on ALS data delivered favourable results for our study environment and so we proceeded with this approach. A canopy height model (CHM) was derived from the ALS datasets at a resolution of 0.3 m. Tree detection was completed using the lidR package (Roussel and Auty, 2018) and several algorithms and settings were trialled until a favourable result was obtained, based on manual inspection of pre-selected regions across both study sites. Following this process, the watershed algorithm with a minimum tree height of 0.5 m was selected for use. The tree detection and delineation algorithm was applied across all AOIs to identify candidate invasive conifers.

Canopy boundaries outputted by the tree detection algorithm were reviewed in the second phase of reference dataset development. These polygons were loaded into a geographical information software (GIS) and visually checked using the UAV imagery and the CHM covering each AOI to identify the polygons containing invasive conifers. The tree detection algorithm did not differentiate between invasive conifers and other trees, shrubs, and objects such as rocks within an AOI. Polygons representing these objects were manually removed from the tree detection reference dataset. In other cases invasive conifers that were not identified by the tree detection algorithm were added or the crown depiction was manually improved. Following extensive review of the polygons we were confident that all visible invasive conifers within the AOIs were accurately digitised. All objects down to 0.5 m were identified by the tree detection algorithm and in the secondary phase all visible invasive conifers were included in the reference dataset. The smallest trees identified occupied three to four pixels in the UAV imagery and so had a canopy area of 0.3 - 0.4 m ^{2}. Although this process was time consuming it was deemed to be more rigorous, efficient, and accurate than either collection of a field sample or digitisation of the target invasive conifers without initial tree detection. Both HFP and KFP contained invasive conifers that had been treated with herbicide as part of control measures. These trees were not included in the sample as they had different spectral and structural properties to living trees and identification of living invasive conifers was the primary objective of the study. For each AOI the area occupied by invasive conifers in the reference dataset was used to calculate the percentage cover (Table 5.1).

5.4.9 Developing semi-automated UAV mapping of invasive conifer distributions

Data sets from five AOIs across three distinct sites were available for modelling the distribution of invasive conifers. As there were three AOIs within HFP with independent UAV flights, these were used to test whether models for mapping invasive conifer were transferable within a site. All AOIs were used to test whether models were transferable to other sites with different terrain and vegetation characteristics.

We used maximum Entropy (MaxEnt) distribution modelling (Phillips et al., 2006) implemented via the 'dismo' package (Hijmans et al., 2017) within R (R Core Team, 2018) to provide semi-automated mapping of invasive conifer distributions across all

AOIs. The MaxEnt modelling approach was chosen because it is a one-class classifier that can provide useful predictions of species distribution using presence only data (Kattenborn et al., 2019b; Phillips et al., 2006). This is a suitable framework for our application as the distribution of other vegetation types or objects across the landscape is not of interest. Using a one-class classifier provides significant efficiency as sampling other classes within the AOI is not required as they do not need to be defined in the reference dataset (Elith et al., 2011; Kattenborn et al., 2019b). Although non-target class data is not required by MaxEnt, the model can be configured to account for background samples within the area of interest.

Prior to model development raster stacks containing all predictor variables were resampled to 0.1 m resolution for consistency and to facilitate merging. We investigated the relative importance of different predictor types in the MaxEnt invasive conifer distribution models by reviewing the accuracy of different types of models for each AOI. These included spectral data only (spectral), variables derived from ALS data only (als), and models with both spectral and ALS derived predictor variables (spectral + als). Spectral predictor variables included all bands in the original multispectral imagery and the derived spectral indices.

To provide training and validation data, 2000 random sample points were selected without replacement for each of the following classes. Positive invasive conifer points were sampled from within the bounds of the reference polygons covering invasive conifer canopies and were used for MaxEnt model training. Absence points were sampled from within each AOI in areas outside of the reference polygons and were used in model evaluation. Background points containing both negative and positive samples were selected from across the entire AOI and were used as part of MaxEnt model training. A 10-fold cross validation with 100 repetitions was used to totally separate the randomly sampled locations into training and testing datasets. The cross-validation ensured separation of the training and validation datasets and the 100 repetitions ensure that variance associated with a given sample was stabilised. Following initial testing of different numbers of repeats 100 repetitions were found to be adequate to provide stable estimates of model accuracy.

Variable importance was assessed using permutation importance (Phillips, 2006) and was used to remove unimportant predictors in each model based on an initial inspection of importance scores. The utility of the different predictor types (spectral, als) and the combined set of predictors (spectral + als) was assessed by comparing the accuracy of models fitted with these predictors when assessed against the independent testing sample in each fold of the cross validation.

5.4.10 Accuracy assessment and statistical analysis

Several accuracy statistics were used to assess the accuracy of invasive conifer prediction maps based on the repeated cross-validation. A confusion matrix was produced and used to calculate true positive rate (TPR, also referred to as sensitivity), true negative rate (TNR, also referred to as specificity), false positive rate (FPR), false negative rate (FNR) and the overall accuracy (OA) of the classification. Classification performance for each model was assessed further using Cohen's kappa (Cohen, 1960) (kappa) coefficient. Kappa has historically been a widely used metric for assessing the agreement between two sets of observations. The statistic is generally deemed to be robust because it accounts for agreements occurring through chance alone. However, recent research has suggested that kappa should be avoided in the context of remote sensing studies for several reasons because of its sensitivity to bias and prevalence (Foody, 2020). With this in mind we also calculated the True Skill Statistic (TSS) which is independent of prevalence and has been shown to perform favourably to kappa in a species distribution modelling context whilst still accounting for chance agreement (Allouche et al., 2006).

TSS was calculated using equation 5.3 based on the confusion matrix produced from the repeated cross-validation. Both kappa and TSS range between zero and one with zero indicating an indiscriminate model and one a model with perfect prediction accuracy.

$$TSS = \frac{ad - bc}{(a + c)(b + d)} = Sensitivity + Specificity - 1 \tag{5.3}$$

Where a = number of samples for which presence was correctly predicted by the model, b = number of samples for which the species was not found but the model predicted presence, c = number of samples for which the species was found but the model predicted absence, and d = number of samples for which absence was correctly predicted by the model.

Receiver operator characteristic (ROC) curves were also used to examine the accuracy of the classification. ROC curves are graphical representations of the accuracy of binary classifiers. The true positive rate (sensitivity) is plotted on the y-axis and the false positive rate (specificity) forms the x-axis. The ROC curve is plotted by calculating the cumulative distribution function on both of these axes with a diagonal reference line plotted to indicate where classification is no better than chance. The area under the curve (AUC) can be calculated from ROC curves and is used to quantify classification quality. AUC values for ROC curves vary between 0.5, where classification is no better than chance, to 1, indicating a perfect classification. ROC curves were plotted and AUC was calculated using the evaluate function of the dismo (Hijmans et al., 2017) R package.

5.4.11 Testing model portability

To examine model portability each model was used to predict invasive conifers for all other AOIs. As there were three available datasets at HFP these were used to examine model portability within a site. To that end, each model developed using a given dataset was applied to predictor variables from the other two datasets and validated using the reference data collected in the target areas. Comparing the accuracy of models trained and applied in the same AOI with those trained on one flight and applied to another allowed us to quantify the portability of UAV-based invasive conifer detection maps within a site.

The portability of UAV-based invasive conifer detection models to other sites was also of interest. It was hypothesised that models would provide accurate results when applied to simpler or comparable sites but that models developed in simpler sites would not provide accurate results when applied to more complex environments. To test this all models were used to predict invasive conifer distribution across all other available AOIs. Our experimental design allowed us to test this by applying models developed in simpler settings to complex environments and those developed in complex environments to simpler sites. In all cases the same accuracy statistics were calculated based on repeated cross validation.

5.5 Results

5.5.1 UAV-based mapping of invasive conifer cover

Model accuracy based on the repeat k-fold cross validation tested within the AOI used for model training is summarised in Table 5.2. Highly accurate models were developed for mapping invasive conifers across all sites. The accuracy statistics calculated showed that the most accurate model was developed using a combination of spectral and ALS predictors at the simplest site LP-1 (mean AUC = 0.98, mean kappa = 0.91, mean TSS = 0.91). The least accurate models were developed in HFP-3 (AUC = 0.84, kappa = 0.57, TSS = 0.59) and KFP-1 (AUC = 0.88, kappa = 0.66, TSS = 0.67). In general, as site complexity increased model accuracy decreased, one exception to this was the medium complexity AOI HFP-3 which had similar accuracy to the most complex AOI in our study (KFP-1).

Across all sites the most accurate models were those developed using both spectral and ALS predictors (mean AUC = 0.949, mean kappa = 0.831, mean TSS = 0.818) and the least accurate were those using spectral data alone (mean AUC = 0.904, mean kappa = 0.704, mean TSS = 0.710). The exception to this was in the simplest site (LP-1) where the model developed using ALS predictors only was equally accurate as those developed with both ALS and spectral data. Models developed using only spectral predictors were less accurate in general but still provided a very high degree of accuracy at LP-1 (AUC = 0.97, kappa = 0.87, TSS = 0.87). Across all sites the accuracy of models developed using only spectral predictors was moderate to high (kappa > 0.6) and would still be useful for mapping invasive conifer distributions.

Table 5.2 Accuracy statistics for the MaxEnt models used to map invasive conifers throughout each study area. Results for models developed using spectral predictors (spectral), ALS predictors (ALS), and a combination of both (ALS + spectral) are presented separately. For each model the area under a ROC curve (AUC), Cohen's kappa (kappa), and the true skill statistic (TSS) are shown.

Identifier	**Model**	**AUC**	**Kappa**	**TSS**
HFP-1	spectral	0.91	0.68	0.69
HFP-1	als	0.95	0.81	0.81
HFP-1	spectral + als	0.96	0.83	0.83
HFP-2	spectral	0.92	0.73	0.74
HFP-2	als	0.93	0.77	0.78
HFP-2	spectral + als	0.96	0.85	0.85
HFP-3	spectral	0.84	0.57	0.59
HFP-3	als	0.90	0.73	0.75
HFP-3	spectral + als	0.91	0.74	0.75
KFP-1	Spectral	0.88	0.66	0.67
KFP-1	ALS	0.90	0.68	0.69
KFP-1	Spectral + ALS	0.93	0.74	0.75
LP-1	Spectral	0.97	0.87	0.87
LP-1	ALS	0.98	0.91	0.91
LP-1	Spectral + ALS	0.98	0.91	0.91

In addition to the accuracy statistics invasive conifer distribution maps were produced and manually reviewed for all datasets. In most cases the maps were found to provide a good representation of the invasive conifers manually digitised in the reference polygons. However, several instances likely to result in commission and omission errors were observed. The MaxEnt model outputs are provided as a likelihood of a subject pixel belonging to the target class (Figure 5.2) which can be converted from likelihood to presence-absence maps through the selection of an appropriate threshold. Figure 5.2 provides some insight into model performance in the HFP sites which are moderately complex. In the western part of HFP-1 (Figure 5.2 a and b) there are areas dominated by non-target shrubs including *Ulex europea* that are clearly visible in the RGB image. These have correctly been assigned a low likelihood of being invasive conifers (Figure 5.2 b). In HFP-2 (Figure 5.2 c and d) an area of invasive conifers where herbicide has recently been applied is evident by the red colour in the RGB image. Herbicide treated trees were excluded from the reference dataset in all sites and it is clear from the colour ramp in Figure 5.2 d that that these have been classified with a lower likelihood of being invasive conifers. These results provide some confidence in the predictive performance of the invasive conifer distribution models within these areas.

5.5.2 Transferring models within a site

The three AOIs within the HFP study site were used to examine model portability within a study site by using the mean accuracy statistics for each model when validated against the other two AOIs. When models were validated using data from different AOIs within the same site, model accuracy was found to be similar to that achieved when validation was undertaken using the same dataset used for model training. Across all model types the mean accuracy statistics when validated against data from the same AOI (mean AUC = 0.92, mean kappa = 0.745, mean TSS = 0.752) were slightly better

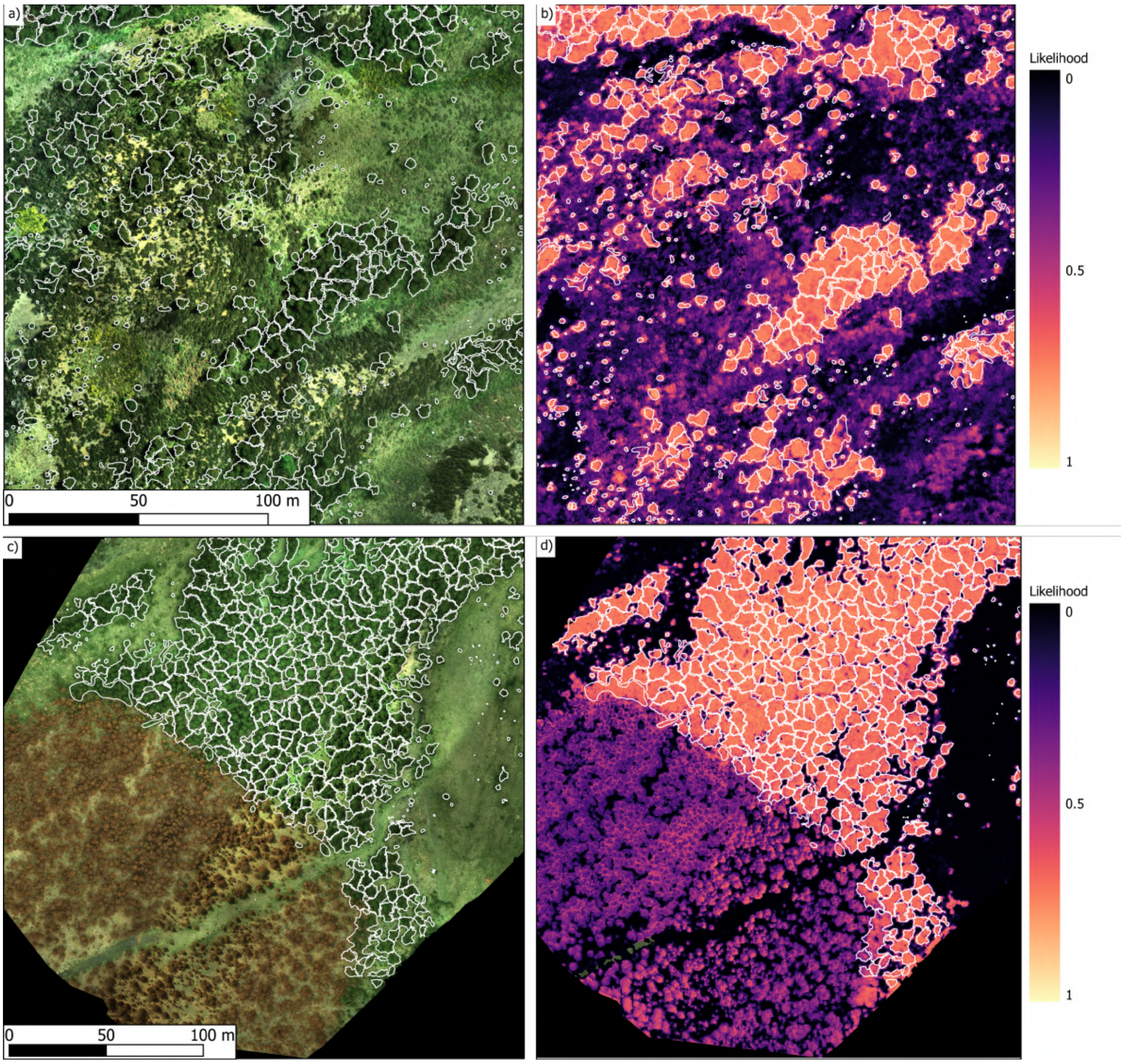

Fig. 5.2 Examples of the outputs from the MaxEnt modelling of invasive conifer distributions for HFP-1 (a,b) and HFP-2 (c,d). Left hand panels show RGB imagery and the right hand panels show the likelihood of the predictions of invasive conifers. All images also show the digitised reference dataset showing the invasive conifer canopy area outlines. Invasive conifer distribution maps are produced with a combination of ALS and spectral predictors.

than the accuracy statistics for validation using an alternative AOI within the same study site (mean AUC = 0.898, mean kappa = 0.695, mean TSS = 0.703). Invasive conifer distribution models were highly accurate both when validated using the same dataset used for model development or an alternative AOI within the same study site. The AUC statistic was less sensitive to validation using data from an alternative

AOI (mean change = 0.022) compared to kappa and TSS (mean change kappa = 0.049, mean change TSS = 0.048). The relative performance accuracy of models using different sets of predictors remained the same whether they were validated against data from the same AOI used to fit the model or from an alternative AOI. In both cases models that used a combination of spectral and ALS predictors were the most accurate followed by ALS only and the spectral only predictors.

The magnitude of the change in accuracy when models were validated against an alternative AOI compared to the base model fitting AOI was greater for spectral (mean change AUC = 0.0265, mean change kappa = 0.0588, mean change TSS = 0.0579) and spectral + ALS models (mean change AUC = 0.0213, mean change kappa = 0.0548, mean change TSS = 0.0531) than for models developed with ALS predictors only (mean change AUC = 0.0174, mean change kappa = 0.0347, mean change TSS = 0.0340). The magnitude and direction of accuracy change was not consistent between models developed from different AOIs (Figure 5.3). Models developed in HFP-1 and HFP-2 were slightly less accurate when applied to other AOIs for accuracy assessment but models developed in HFP-3 became marginally more accurate. This trend was apparent across all model types and is evident by the position of each datum relative to the horizontal dashed line in Figure 5.3. Spectral models developed in HFP-2 displayed the greatest decrease in accuracy when applied to other HFP AOIs and spectral models from HFP-3 displayed the greatest increase in accuracy. Models developed using ALS predictors in HFP-2 were the most stable when transferred within a site as the magnitude of change between the base model and the transferred model was very close to zero across all accuracy statistics (Figure 5.3).

Prediction maps showing invasive conifer occurrence likelihood produced by models developed in other AOIs were mapped over each recipient AOI and compared to the base models. Difference rasters were calculated by subtracting the donor map predictions

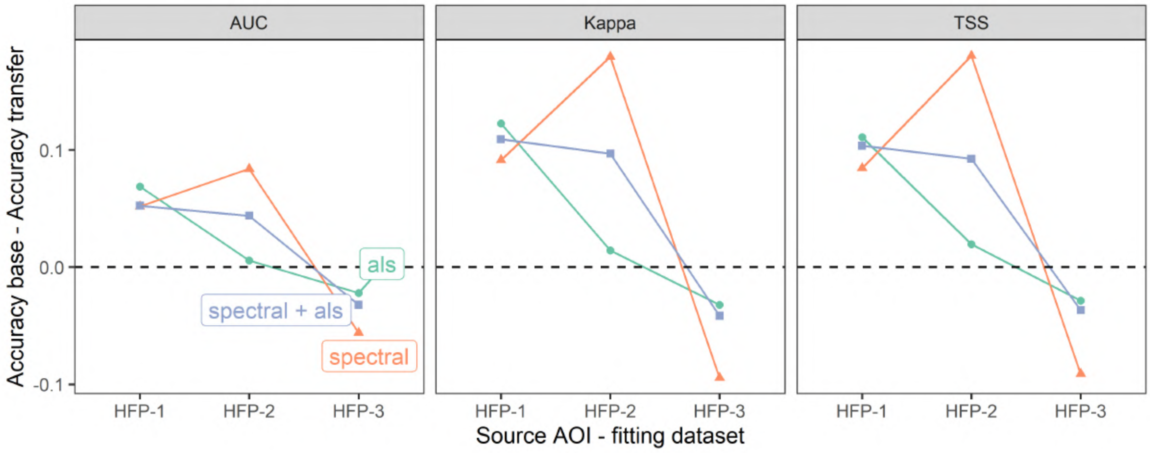

Fig. 5.3 Magnitude of change in accuracy statistics for UAV-based MaxEnt models when validated using data from other AOIs (accuracy transfer) within the same study sate compared to validation using the same AOI as used for model fitting (Accuracy base). The dashed horizontal line is at 0 indicating no change in accuracy. Results above this line indicate a decrease in accuracy when applied to a different AOI and results below this line show an increase in accuracy compared to the base scenario.

from the base map predictions produced to examine the pattern of agreement and disagreement between base and transferred prediction maps (Figure 5.4). In the prediction difference maps white areas have a perfect correspondence between the base map and the donor map developed in a different AOI. Areas where the likelihood of invasive conifer presence is higher in the base maps are greener and areas where the likelihood of invasive conifer presence is higher in the donor maps area more purple. Figure 5.4 shows that the HFP-2 donor model is more similar to the base model (HFP-1) than the HFP-3 donor model when applied to HFP-1.

The error patterns from the different donor datasets are also apparent. All three maps correctly identify the areas dominated by invasive conifers and even scattered individuals or small clumps on the river plain were correctly identified by all three models. Two areas where invasive conifers have been herbicide treated in the north-west of HFP-1 AOI (Figure 5.4 (a) red circles) were correctly given a low likelihood of being invasive conifers by both the base model and the donor model developed in HFP-2

(Figure 5.4 b). The purple colours in these patches in Figure 5.4 c indicate that the model developed in HFP-3 incorrectly assigned these areas with a higher likelihood of being invasive conifers than the base model. It is notable that there were no herbicide treated areas in HFP-3 so this can be considered as an out-of-sample error for the HFP-3 model. A stand of indigenous trees is clearly visible in the north of the AOI (Figure 5.4 (a) yellow circle) and both of the donor models assigned a higher likelihood to invasive conifer presence in this area than the base model which differentiated these trees from invasive conifers more accurately. The green colours in both difference maps are associated with riparian vegetation adjacent to the river running through the eastern side of the AOI. This indicates that the donor models have given these areas a slightly lower likelihood of being invasive conifers than the base model and so have greater accuracy in this instance.

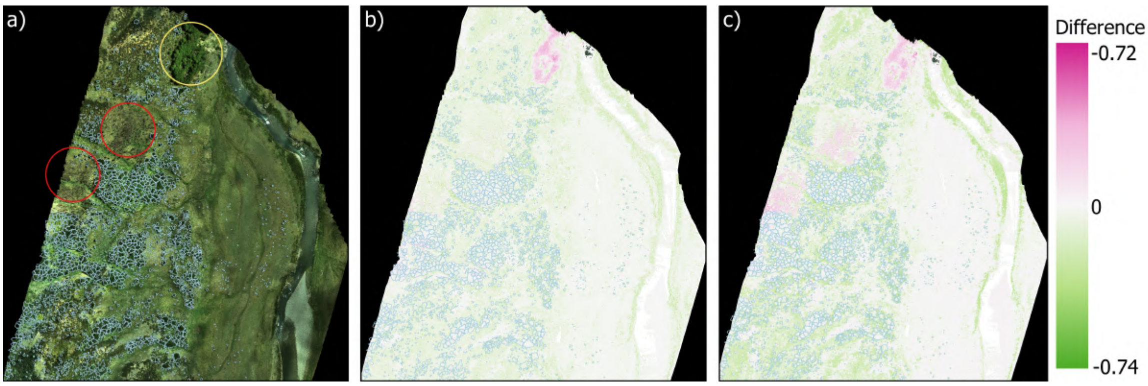

Fig. 5.4 An RGB image showing an area of HFP-1 (a) and difference rasters showing the magnitude of difference in invasive conifer likelihood (base model - donor model) for HFP-2 model applied to HFP-1 (b) and the HFP-3 model applied to HFP-1 (c). Invasive conifer canopy polygons are shown as light blue outlines. The red circles in panel (a) show areas where invasive conifers have been treated with herbicide, the yellow circle in panel (a) shows a stand of indigenous trees within the AOI.

5.5.3 Model transferability between sites

In total 14 models were transferred to and validated against data from AOIs in different sites. On average, across all model predictor types, models validated using datasets from different sites were less accurate (mean AUC = 0.836, mean kappa = 0.619, mean TSS = 0.644) than models validated against different AOIs within the same site (mean AUC = 0.879, mean kappa = 0.659, mean TSS = 0.668), or those validated using the same AOI used for model development (mean AUC = 0.922, mean kappa = 0.748, mean TSS = 0.755). Models developed using only spectral predictors were more robust to transfer to another site for validation than those that included ALS data or a combination of ALS and spectral predictors (Table 5.3). Models developed with ALS showed the greatest decrease in accuracy when they were validated against data from other sites (mean decrease in kappa = 0.227) whereas spectral models showed only a marginal decrease in accuracy on average (mean decrease in kappa = 0.012).

Table 5.3 Mean accuracy statistics for the MaxEnt models used to map when validated against the same dataset used to develop the model (Base) and when validated using data from a different site (Intersite). Results for models developed using spectral predictors (spectral), ALS predictors (ALS), and a combination of both (ALS + spectral) are presented separately. For each model the area under a ROC curve (AUC), Cohen's kappa (kappa), and the true skill statistic (TSS) are shown along with the change in accuracy between base and intersite.

Model	Statistic	Intersite	Base	Change
als	AUC	0.766	0.930	0.163
als	kappa	0.543	0.771	0.227
als	TSS	0.603	0.780	0.177
spectral	AUC	0.878	0.890	0.012
spectral	kappa	0.654	0.669	0.014
spectral	TSS	0.660	0.675	0.014
spectral + als	AUC	0.865	0.945	0.080
spectral + als	kappa	0.660	0.805	0.145
spectral + als	TSS	0.670	0.811	0.142

The experimental design allowed the impact of both donor and receiver site complexity on the accuracy of transferred models to be analysed. These results are presented in Figure 5.5 and clearly show that there are accuracy trends that relate to the characteristics of both donor and recipient sites and to the predictors used by the model. There is a general trend for models developed in more complex sites to provide accurate predictions in less complex sites. Conversely, those developed in simpler sites perform worse in the most complex sites (Figure 5.5).

The trend is most marked in models that use ALS predictors only. Models that used ALS predictors only and were developed in the least complex sites provided moderate accuracy in sites with moderate complexity (AUC = 0.71, kappa = 0.5, TSS = 0.56) but extremely low accuracy when applied to the most complex sites (AUC = 0.44, kappa = 0.13, TSS = 0.35). Similarly, ALS-based models developed in sites with moderate complexity performed poorly in the most complex sites (AUC = 0.59, kappa = 0.21, TSS = 0.33) but were highly accurate when applied to the simplest sites (AUC = 0.97, kappa = 0.9, TSS = 0.9).

Models developed with only spectral predictors were the most robust to transfer between sites. Spectral models developed in the simplest site could be transferred to sites with moderate and high complexity with moderate accuracy (Figure 5.5). Spectral only models developed in moderate complexity sites provided high accuracy when transferred to sites with lower complexity (AUC = 0.95, kappa = 0.79, TSS = 0.79) and moderate accuracy when applied to sites with high complexity (AUC = 0.83, kappa = 0.55, TSS = 0.55). Interestingly the spectral only models developed in the simplest site performed better than those developed in moderate complexity sites when they were applied to and validated within the most complex sites. Models developed in the most complex sites provided very high accuracy when applied in the simplest sites and moderate to good accuracy when applied to moderately complex sites (Figure 5.5). Although models developed with a combination of spectral and ALS predictors were the most accurate when validated within their source AOI they were less stable to transfer to more complex sites than models developed using spectral data only. However, models with both spectral and ALS predictors provided very high accuracy when transferred to the least complex site (AUC = 0.95, kappa = 0.79, TSS = 0.8).

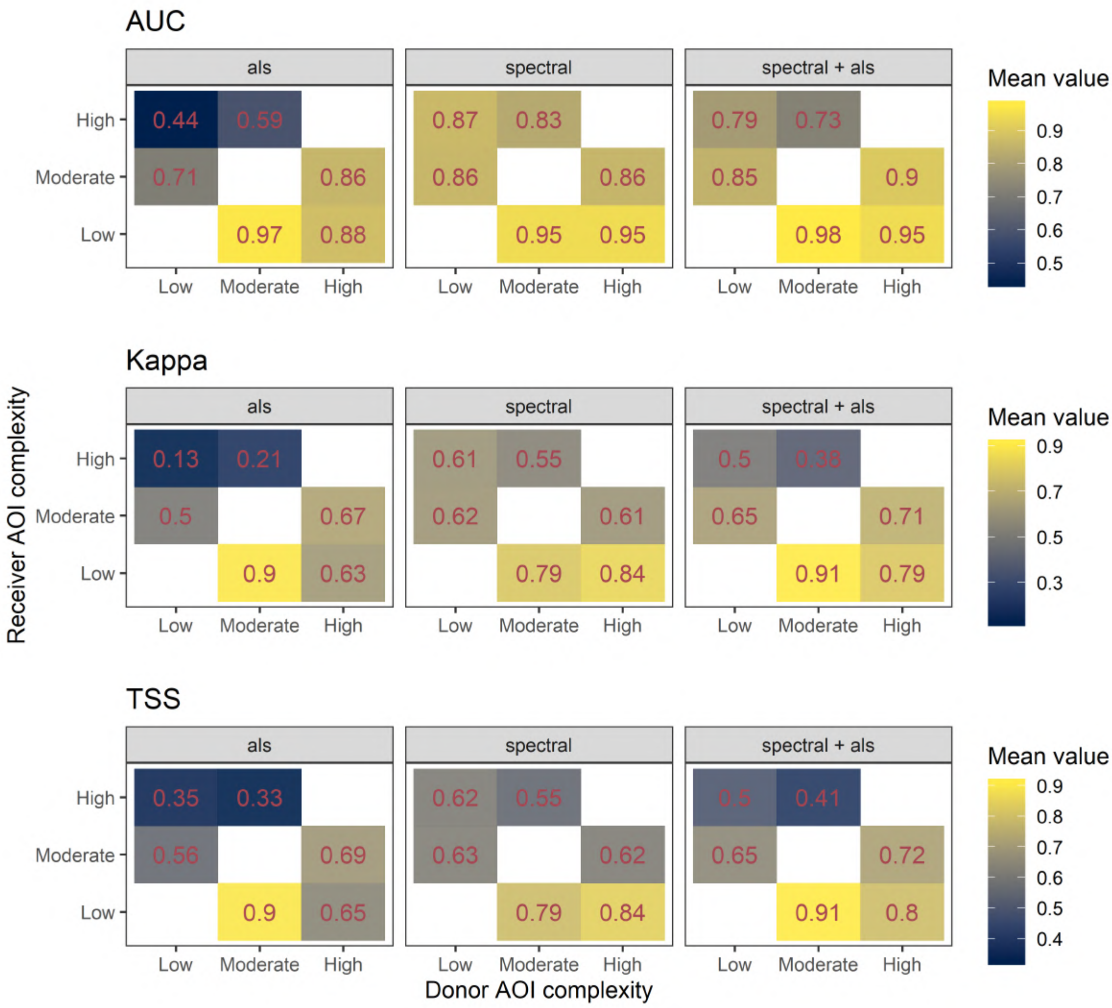

Fig. 5.5 Heat maps showing mean accuracy statistic for transferred models developed and applied to sites of varying complexity. Each panel shows statistics for models developed with a different set of predictors.

5.6 Discussions

In this study we developed numerous MaxEnt invasive conifer distribution models for a range of vulnerable environments within New Zealand. The models produced were generally of a moderate, high, or very high accuracy depending on the complexity of the study site under investigation. These models were used to produce maps that are usable and practical outputs for managers engaged in invasive conifer control activities. Due to the flexibility of UAV deployment these can provide a valuable tool for managers and a useful augmentation to satellite or piloted aircraft based remote sensing.

We compared the accuracy of models developed with spectral predictors, ALS-based predictors, and those developed with a combination of both predictor types. Our results clearly showed that in most instances the models with the greatest accuracy included combinations of both spectral and ALS-based predictor variables. This result is logical as the fusion of these datatypes facilitates the detailed description of both the three-dimensional structural properties and the spectral properties of the target objects. The exception to this finding occurred at the simplest study site (LP-1) where models developed with either spectral only or ALS only predictor variables performed as accurately as models developed with a combination of both. This finding is consistent with the results of previous work at LP-1 (Dash et al., 2019c) and we believe is the result of simplicity of the vegetation composition at this site. The site is dominated by tussock grassland and, excluding invasive conifers, is devoid of larger shrubs and trees. This means that a near-perfect classification can be achieved with either sensor type, thus precluding the need for fusion. At all other sites the combination of ALS and spectral predictors is clearly advantageous for mapping invasive conifers.

Model accuracy generally decreased as site complexity increased although models with adequate predictive accuracy for prediction were developed at all sites included in the study. An exception to this trend was observed at HFP-3 where model predictions were less accurate than the most complex site (KFP-1). We believe that this observation can be explained by two factors, firstly, the HFP-3 AOI had greater tree and shrub diversity than the other AOIs in HFP. Secondly, the UAV orthomosaic at HFP-3 exhibited more geometric distortion than those at HFP-1 and 2 and this might have been a causal factor in both an increase in model error and an increase in measurement error in the reference dataset. Further research is required to study and better understand the interaction between image quality and reference datasets collected from remote sensing data. Image quality and site complexity are interrelated, and they affect the quality of the fitting dataset, model accuracy, and the validation dataset. The relative contribution of these factors cannot be disentangled using our datasets but future studies could examine this further.

Developing the reference dataset at the more complex sites was more time consuming as the technician had to spend more time interpreting the presence or absence of invasive conifers in a more challenging scene. However, the pattern would be similar if field data collection was used to form the reference dataset as navigation and movement would be difficult in the more complex sites and as a result data quality would likely be reduced. Further research is required to investigate whether there is an advantage to field data collection or whether desktop approaches like those employed in this study area are an adequate replacement. There is no doubt that, from both a cost and a safety perspective, the desktop approach is preferable. However, in some scenarios there will be many target objects that are too small, unclear in imagery, or hidden and so cannot be identified in a desktop exercise. In these cases, field sampling may improve reference dataset accuracy but may also introduce additional errors such as GNSS inaccuracy and measurement error.

Invasive conifer distribution maps were produced from all models and assessed both through accuracy statistics and through reviewing the likelihood surfaces produced alongside the UAV imagery. In this manner it was observed that in most instance the maps reflected the invasive conifer distributions reasonably accurately although there were some errors of omission and commission. These tended to be caused by site specific factors unique to each instance and do not detract significantly from the practical utility of the maps produced. Elsewhere map performance was found to be encouragingly accurate with good distinction of invasive conifers from non-target vegetation and other objects observed in many cases.

We tested whether models were portable to other AOIs containing independent non-overlapping UAV data within the same site. We found that the invasive conifer distribution models we produced were portable within a site dominated by similar terrain and a consistent background vegetation composition and structure. This was evidenced by the relatively minor magnitude of the changes in accuracy when models were validated using data from areas that were not used to develop the model. Of the three sites examined in the intra-site portability experiment we found that two sites (HFP-1 and HFP-2) experienced a small decrease in accuracy whilst the third (HFP-3) showed a small increase in accuracy. This was probably due to the slightly greater complexity and worse image quality in HFP-3. In any case the changes in the validation statistics were relatively minor leading us to conclude that the models developed are robust to application to different AOIs within the same environment.

We also tested the portability of models to other sites with different terrain and vegetation conditions from the site used for model training. We found that the accuracy of models transferred to different sites was lower than those validated against data from the same AOI used during model development and from models transferred to different AOIs within the same site. We found that models developed using spectral predictors were more stable to transfer to different sites regardless of the properties of the source and recipient site. Models using either ALS predictors only or a combination of ALS and spectral predictors were substantially less accurate when applied to and validated against data from a different site.

We examined the relationship between donor and receiver site complexity and model accuracy. We found that there was a general trend that models developed in more complex sites produced accurate results when validated using data from more simple sites and, conversely, models developed in simple sites were less accurate when validated using data from more complex sites. However, this was most apparent in models developed with ALS only as these models can produce good results in simplistic environments but are inaccurate and clearly unsuitable for use in more complex areas. Spectral models were found to be the most robust to an increase in complexity in the receiver site compared to the complexity of the site used for model development. Even spectral models developed in the least complex site still provided moderate accuracy when validated against data from the most complex site. Models developed using a combination of spectral and ALS predictors were less stable to transfer to sites with different conditions to the site used for model development. The greater stability of spectral models probably stems from the fact that the spectral properties of invasive conifers do not vary greatly between sites and are useful for differentiation regardless of the background conditions. By contrast, ALS data is probably only for differentiation when there are substantial differences in height and structure from the background vegetation. This is definitely the case in the simple tussock dominated site (LP-1) where invasive conifers constitute the majority of tree and shrub vegetation. At HFP and KFP the background vegetation includes significant quantities of similar size non-target trees and shrubs that cannot be differentiated from invasive conifers using ALS data alone.

The findings of our study have significant implications for mapping invasive conifers using UAV data. We have clearly shown that highly accurate UAV-based models of invasive conifer distribution can be developed across a range of site complexities. Our results also suggest that models can be transferred between AOIs within a site with some confidence. We observed only a limited reduction in accuracy when transferring models to different AOIs within a site. The implications of this result mean that accurate models developed in one AOI can be re-used without the need for the collection of an additional reference dataset or extra model development. This could lead to considerable efficiencies and cost savings. Careful consideration must be given to the sensor type and the properties of both the donor and receiver environments before transferring models between sites. Our results suggest that models can be safely transferred from more complex to simpler sites in most instances and that models that use spectral data only are more generalisable than those that include ALS predictors. We also found that spectral models can be transferred from simpler to more complex sites with a reasonably small decrease in accuracy that might be deemed acceptable depending on the application and the available budget. Although these findings are also relevant to other forms of aerial imagery, they are particularly relevant to UAV data due to the targeted nature of UAV data collection. During UAV sampling design the choice must be made about the properties of the AOI to be included in the flights. Application of our findings will lead to greater efficiency and higher accuracy.

5.7 Conclusion

In this experiment we used UAV-based models of invasive conifer distribution from five different AOIs to test the hypothesis that UAV-based models of invasive conifer presence could be transferred to datasets that were not used for model development. We found that when highly accurate models are developed these can be transferred within a site to AOIs with similar characteristics with only a marginal decrease in accuracy. We found that models can be transferred from more complex sites to less complex sites with a limited decrease in accuracy but that models developed in simpler sites could not be transferred to more complex sites without an accuracy penalty. In many instances the decrease in accuracy would be so large that model predictions become useless. We also found that models developed with spectral predictors were the most robust to transfer, relative to those developed from ALS data. These results have important implications for model reuse and for procedural efficiency for researchers and managers engaged in invasive conifer mapping and management.

5.8 Acknowledgements

This research was funded as part of the Winning Against Wildings Project funded by the New Zealand Ministry for Business Innovation and Employment (Contract Number C09X1611) and the Forest Growers Levy Trust. Additional funding was also provided by the New Zealand Ministry for Primary Industries post-graduate scholarship fund. The authors are extremely grateful to Robin Hartley, Ben Morrow, and Toby Stovold of Scion who collected the UAV data used in this study.

5.9 Author contributions

JPD conceived of this study, wrote all software, processed all data, carried out all analysis, and wrote the original draft of the manuscript. All other authors reviewed, edited, and made contributions to the text of the final version.

Chapter 6

Monitoring the progression and management of exotic conifer invasions using the spectral time series available in the Landsat archive

6.1 Preamble

Long term time series satellite imagery is now available thanks to the opening of the Landsat archive. This valuable dataset has provided a source for new insight into changing patterns of land cover and the human activities and policies that influence it. This represents a valuable tool to monitor the effect of different activities on land use and land cover patterns through time. By mining this data source researchers can offer insight into actions have had positive, or deleterious, effects on desired land cover outcomes. Through monitoring the spectral trajectories of pixels in the Landsat archive land cover changes can be identified either through manual interpretation, or automatically using time series models. A significant body of research now supports the successful application of automated approaches to detect both gradual and abrupt changes in spectral trajectories that relate to natural and anthropogenic drivers of landscape change. The research presented in this chapter summarises an investigation into whether similar techniques can be applied to track historic vegetation changes associated with invasive conifer spread and management. This offers a new and useful tool enabling the impacts of previous management interventions on land cover outcomes to be evaluated. Several technical components need to be in place and methods developed and tested for this to be realised. The suitability of the Landsat archive for this task in New Zealand was reviewed, high-performance computing options to facilitate the large scale image analysis required were investigated, algorithms that could potentially provide automated detection of changes in invasive conifer related land cover patterns were identified, and an extensive case study to test the viability of the approach was developed.

This study was developed to address RQ3 in this thesis and has been prepared as a manuscript for publication that is currently undergoing peer-review.

Dash, J.P., Paul, T.S.H., Morgenroth, J., Watt, M.S. (2020). Tracking *Pinaceae* invasions and their management in New Zealand's high-country using time series Landsat imagery (2000 - 2019) and the LandTrendR algorithm. In review.

6.2 Abstract

Invasive exotic conifers are significant plant pests across large areas of the southern hemisphere including New Zealand. These trees have considerable deleterious impacts on indigenous biodiversity, affect ecosystem function, and can result in economic losses in affected areas. Current research aims to develop remote sensing methods to identify their current distribution and invasion state so that control methods can be planned and executed more efficiently. The invasive nature of many exotic conifer species has long been recognised in New Zealand and focused nationwide control efforts have been underway since the year 2000. However, current estimates of spread rates, patterns, and the success of control efforts are incomplete or anecdotal due to the previous lack of national assessment standards. In this study we propose a methodology for monitoring the historic spread and control of invasive exotic conifers across large areas of New Zealand using two decades of imagery from the Landsat archive. The implementation of the LandTrendR algorithm within the high-performance computing infrastructure of Google Earth Engine was used to provide initial temporal segmentation of areas where vegetation changes may have been associated with invasive conifer encroachment or control. In a subsequent process pixel-based temporal segments were amalgamated into contiguous patches and used to fit a random forest classification model to attribute the causal agent of the vegetation changes identified by LandTrendR. Independent validation of the change agent attribution model showed moderate overall accuracy for both invasive conifer control (User's accuracy = 0.70, Producer's accuracy = 0.78) and invasive conifer encroachment (User's accuracy = 0.50, Producer's accuracy = 0.83). However, substantial inter-class confusion was evident within the model with issues caused by the inability of the spectral trajectory information to accurately separate changes associated with invasive conifers from similar changes associated with other vegetation types. The random forest attribution model was used to map aspects of changes associated with invasive conifer encroachment and control across a heterogeneous 62,164 km^2 area of New Zealand's mountainous South Island. Error

sources within the maps produced were considered in detail and examples of how this new information could be used by stakeholders were discussed.

6.3 Introduction

6.3.1 Background

Biodiversity loss is a global challenge caused by a myriad of factors including habitat loss, fragmentation, and modification through the introduction of exotic species. Mitigating biodiversity loss is a pressing issue and a key sustainable development goal identified by the United Nations (UNHCR, 2017). During the Anthropocene, the ubiquity of human trade and migration has led to the widespread distribution of exotic plants in many areas (Dash et al., 2019b; Kueffer, 2017; Meyerson and Mooney, 2007). In some environments trans-located plants have become invasive and can out-compete and replace existing vegetation (Richardson and Berlyn, 2002) impacting upon biodiversity and the provision of ecosystem services (Simberloff et al., 2013; Vaz et al., 2018b). Outside of areas with high biodiversity value invasive plants regularly reduce the productivity of food or fibre producing areas with significant economic consequences (Velarde et al., 2015).

Exotic trees are the foundation of the commercial plantation forestry sector in many parts of the world and are critical to meet the current and future global timber demand. These forests also contribute significantly to carbon sequestration (Monge et al., 2018), erosion control (Sidle et al., 2006), and provide substantial societal value (Yao et al., 2012). In the southern hemisphere fast-growing exotic conifers (principally *Pinaeceae*) constitute many productive plantations and large areas in several countries have been established for timber production. The evolutionary history of these species mean that they are prone to invading disturbed land via self-sown seeds and may have a transformative effect on indigenous ecosystems (Nunez et al., 2017) that is particularly problematic in grassland or shrubland areas (Nunez et al., 2017; Pauchard et al., 2016; Rundel et al., 2014). Extensive invasions have been noted in several southern hemisphere countries (Richardson and Higgins, 1998) where documented deleterious effects include depletion of water resources (Le Maitre et al., 2002), ecosystem service provision (Dickie et al., 2014), and social and cultural values (Greenaway et al., 2015).

In New Zealand, exotic conifers have invaded significant areas of indigenous and semi-indigenous grass and shrublands and now affect an estimated 2M ha primarily in the mountainous areas of the South Island (Te Waipounamu) (NZFOA, 2016). The affected area is already equivalent to the national forest plantation estate and is estimated to be expanding at a rate of 6% per year (Anon., 2011). Without coordinated control efforts this spread will compromise vast areas with high ecological, cultural, and economic value. To help address this challenge research efforts into detection, monitoring, and control of invasive conifers are underway (Anon., 2011). Control methods rely upon herbicide application and mechanical removal of trees across large remote areas of frequently mountainous terrain. The control of invasive conifers in such areas is expensive (Nunez et al., 2017), can have unintended ecological and social impacts, and has variable success (Paul and Ledgard, 2009). To improve the efficiency and efficacy of control efforts new datasets are required that allow the quantification and quality assessments of such efforts to better inform management practices at various scales. To support this a range of remote sensing methods are being developed to monitor both the current extent of affected areas and the success of control efforts (Dash et al., 2017a, 2019c; Sprague et al., 2019). The weed potential of exotic conifers has been noted since at least the 1960s (Benecke, 1967) and localised control efforts have been underway for more than two decades. Only anecdotal evidence describing the rate of spread into new areas and the success of the past control methods is currently available. Rigorous new methods are required to quantify the rate of infestation spread and the success of historical management activities. Such methods will enable land managers and researchers to better focus their resources on the most effective management activities, the improvement of control methods that show the greatest promise, and a better understanding of invasive conifer spread patterns and drivers at the landscape scale. Single date remote sensing can only provide information about the current distribution and health status of invasive trees. time series remote sensing techniques can potentially illuminate historical patterns and provide sequential information offering new insight.

Detecting landscape changes is an important application of remote sensing analysis (Kennedy et al., 2015) and the availability of repeatedly-captured satellite imagery from long lived Earth observing missions such as Landsat provides a unique tool for this task. Following a data access policy change in 2008 (Woodcock et al., 2008) access to the Landsat imagery archive was made available completely free of charge. This change resulted in a major shift in the use of the Landsat archive for many activities (Wulder et al., 2012) and the continued free and open access to this dataset is vital to support sustainable development and land management goals (Zhu et al., 2019b). Since the opening of the Landsat archive, many new Landsat time series-based approaches have emerged that either use annual representative imagery or make use of the temporal variability in collections of images (Pasquarella et al., 2016). Landsat time series data have been successfully used to map both abrupt and gradual landscape changes throughout the world, at various scales, and numerous algorithms have been developed to automatically detect change (Zhu, 2017).

LandTrendR (Landsat-based detection of trends in disturbance and recovery) (Kennedy et al., 2010) is a well-established approach for modelling change detection within the Landsat archive. The LandTrendR algorithms use a temporally stabilised time series of Landsat images to identify the timing, magnitude, and duration of vegetation disturbances or gains at the pixel scale (Kennedy et al., 2015, 2010). The algorithm has recently been implemented in the cloud-based platform for planetary-scale geospatial analysis Google Earth Engine (Kennedy et al., 2018a) (hereafter this implementation is referred to as LT-GEE) broadening accessibility to LandTrendR and the entirety of the Landsat archive. Since its development LandTrendR has been applied to a wide range of applications including monitoring insect damage to forest stands (Hudak et al., 2013; Liang et al., 2014), forest fire severity and post-fire recovery (Martinez et al., 2017; Reilly et al., 2017), vegetation disturbance in high-biodiversity areas (Cabezas and Fassnacht, 2018; Fragal et al., 2016), the recovery of abandoned industrial areas (Yang et al., 2018), monitoring cropland conversion rates (Zhu et al., 2019a) and selective logging in tropical forests (Shimizu et al., 2016). LandTrendR has also been integrated into a biomass monitoring system (Kennedy et al., 2018b), and used for monitoring changes in the Arctic permafrost (Runge and Grosse, 2019). The range of applications are testament to the flexibility of the approach; however, no research has assessed the capacity of an approach based on LandTrendR to monitor the spread and control of invasive plants.

Once land cover changes in the Landsat archive have been identified, attributing the causal agent of the observed changes can help refine the maps produced and add value to the information provided. Attribution of the causal agent of change can enable land managers and policy makers to better understand the impact of actions and policies on resulting land cover patterns (Kennedy et al., 2015). This can help ensure that ecosystem service provision is optimised to meet the many, and commonly diverging, demands of different actors and activities that rely on an ecosystem's functions (Mason et al., 2017). The causes of landscape-scale changes are also of fundamental scientific interest as they can reveal the overarching agents and pressures driving the change process (Kennedy et al., 2015). These may include changes associated with increased storm activity, urbanisation, or agricultural conversion associated with increased population pressure, or changes in vegetation structure due to the introduction of exotic alien plants which may be exacerbated by a myriad of factors. Consistent and repeatable methods for detection and attribution of landscape changes over large areas and over time can help us define the proximal causes and ultimately provide insight into the broader context of the drivers that trigger the changes observed, the rate of change, and possible responses to the causal phenomena (Kennedy et al., 2015).

In this study a well-validated and flexible change detection algorithm (LT-GEE) was used to develop a monitoring method to track the history of disturbance and vegetation encroachment in a landscape under pressure from the spread of invasive exotic trees. Previous research has made progress towards monitoring the spread of invasive plants from time series satellite imagery (de Sa et al., 2017) but did not take advantage of robust automated detection algorithms and did not seek to provide an accurate attribution of the causal agents of the changes detected. Specifically, in this paper we sought to address the following research questions:

1. Is the Landsat archive for New Zealand suitable for tracking land cover changes associated with historical spread and control of invasive conifers?

2. Can LT-GEE be used to detect the historical encroachment of invasive exotic conifers into natural and semi-natural ecosystems?

3. Can LT-GEE be used to accurately detect management activities in areas invaded?

4. Can the causal agent for the changes detected using LT-GEE be attributed and used to differentiate management activities from other vegetation management activities?

5. Can a detailed history of the encroachment and management of invasive conifers in the study area be developed and made available as a tool to better inform policy decisions and management activities?

6. Is the accuracy of the results adequate to provide useful information to stakeholders?

6.3.2 High Performance Computing Options

Due to the vast size of the Landsat archive the computational requirements for processing time series imagery are intimidating. Until recently there was limited availability of computing with access to the data and with sufficient scale and power for data processing in reasonable time frames. Several groups have developed and deployed super computing frameworks to enable processing. Remote sensing researchers owe a considerable debt to those groups who undertook these efforts but access to these systems comes at a significant financial cost and some expertise barrier to entry. In recent years, a number of technology companies have undertaken to provide high-performance computing capacity to users using a fee for access business model. These include offerings from Amazon (Seattle, Washington, USA), Microsoft (Seattle, Washington, USA) and Google (Mountain View, California, USA). The solutions offered by all of these companies have the capability to provide suitable analysis platforms of sufficient size and scale to work with the Landsat archive. However, the option provided by Google is the most appealing as it includes a geospatial computing facility specifically designed to enable scientists by providing them with the tools to interact with large spatial data stores and to access exceptionally large and highly parallel computing. The service is also available free of charge for research purposes.

Google Earth Engine (GEE) is a cloud-based platform that allows planetary scale geospatial analysis of satellite imagery and provides users with access to Google's computational facilities free of charge (Gorelick et al., 2017). GEE users can access an extensive data catalogue currently housing over six petabytes of data. The sources of data in the catalogue are varied and include the entirety of the Landsat archive, data from ESA's Copernicus programme, and global land cover and climatic datasets. Users can interact with GEE via JavaScript or Python libraries and this provides access to the global data catalogue and Google's massive parallel processing power. A simplified version overview of the GEE architecture is shown in Figure 6.1.

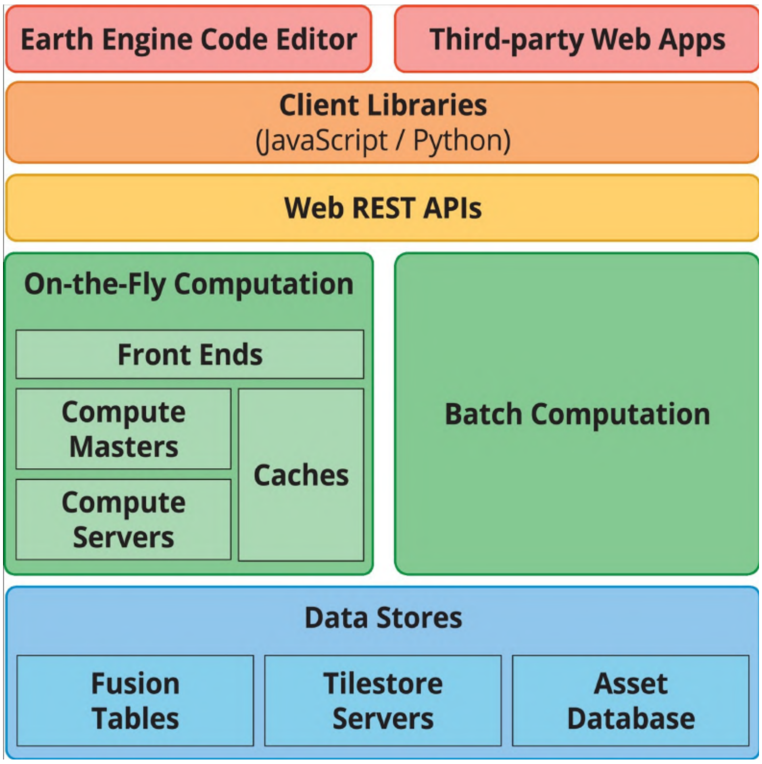

Fig. 6.1 A simplified system architecture diagram of the Google Earth Engine. Reproduced from (Gorelick et al., 2017)

Access to GEE provides considerable research opportunities for New Zealand including access to the GEE data catalogue. Processing tasks using GEE take minutes to complete, as opposed to days or weeks, and can provide useful insights for many areas of research. The API includes an extensive array of functions for image processing, transformation, and classification tasks. The example below (Figure 6.2) shows a composite mosaic of Landsat 8 imagery covering New Zealand in 2017. Following application of a cloud mask all images within New Zealand's geographic area were combined to provide a seamless single image. Simple access to the tools to develop datasets of this type has profound implications for researchers seeking to better understand changes in New Zealand's vegetation and land surface over time.

Fig. 6.2 A cloud free mosaic generated from Landsat 8 imagery generated using Google Earth Engine.

6.4 Methods

6.4.1 Description of the Landsat Archive for NZ

The density of images in the Landsat archive varies for different locations around the world. The value of the dataset within a given nation or region is related to its coverage, completeness, and the longevity of data availability. To understand the history of spread, management, and impacts of invasive exotic conifers in New Zealand a detailed time series of Landsat imagery is required. The Landsat archive has been shown to be a valuable resource for both scientific and management activities throughout the world. However, the Landsat archive for New Zealand has not yet been documented and its potential for spatially explicit monitoring of changes associated with changes in forest cover and the spread and management of invasive conifers has not been explored.

The United States Geological Survey (USGS) stores metadata for the entirety of the Landsat archive and make this available for users to query. This data store was interrogated to extract the metadata for all acquisitions that cover the North or South Island of New Zealand. Data was downloaded separately for Landsat 1-3 (Multispectral Scanner or MSS), Landsat 4-5 (Multispectral Scanner and Thematic Mapper or TM), Landsat 7 (Enhanced Thematic Mapper or ETM), and Landsat 8 (Operational Land Imager or OLI). A spatial query was produced to extract the metadata associated with these images as a series of shapefiles covering New Zealand's main islands. An R script (R Core Team, 2018) was developed to merge, visualise, and summarise both the temporal and spatial coverage of the New Zealand Landsat archive following a methodology similar to that described for an exploration of the Landsat archive in Finland (Saarinen et al., 2018b).

6.4.2 Study area

The study was conducted across a 62,164 km^2 area of New Zealand's South Island. The boundaries of the study area were defined in previous research (Weeks et al., 2013). The area included large contiguous areas of indigenous and exotic grasslands, natural forests, exotic conifer plantations, and other land cover types within the mountainous areas of New Zealand's South Island (Figure 6.3). This study area was selected as it was large enough to test the performance of LT-GEE and contains a significant amount of biologically and culturally valued landscapes currently affected by, or at risk from, invasive conifers. Furthermore, the area included several sites where management of invasive conifers had been actively undertaken since the year 2000.

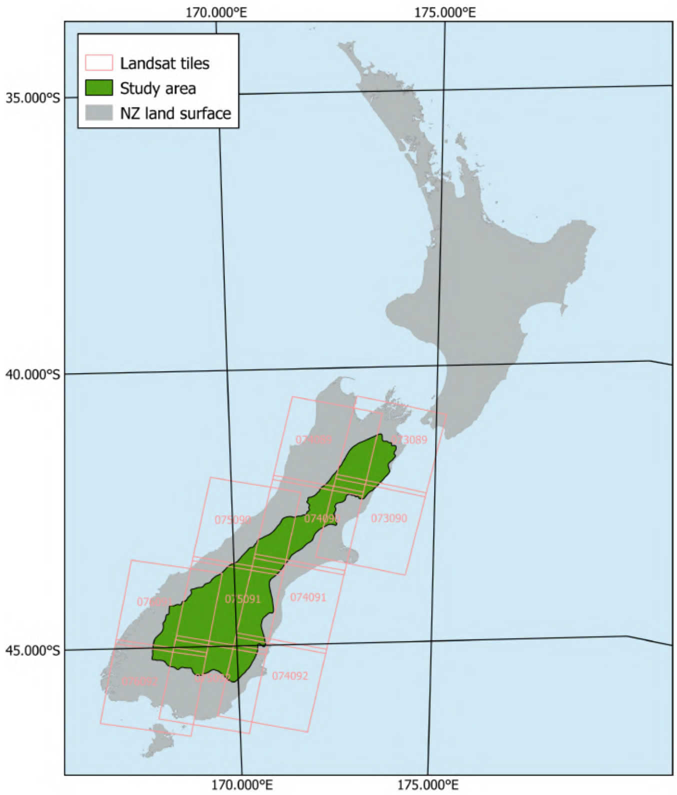

Fig. 6.3 The location of the study area within New Zealand's South Island and the Landsat tiles covering the study area

Land cover within the study area and area of interest was defined using a pre-existing land cover classification developed in previous research providing a land cover database (LCDB) for New Zealand (Newsome et al., 2018). The study area comprised 12 land cover classes (Figure 6.4) including several vulnerable areas such as low-productivity grasslands. The land cover classification was simplified from the original 12 classes into four; natural forests, planted forests, low-producing grasslands and shrublands, and other. Natural forests were then excluded from the study area as this land cover has very low vulnerability to invasion by exotic conifers. High-producing grasslands, cropland, and urban settlements were excluded from the sampling population as they are not subject to exotic conifer invasions and as the short term changes in land cover can produce false results due to ephemeral changes in the LandTrendR outputs (Kennedy et al., 2015). A review of the LCDB classification using recent high-resolution satellite imagery revealed that it included significant inaccuracies and so could not be used to exclude areas of plantation forest from the area of interest. Areas classified as planted forest in the LCDB included many grassland areas adjacent to plantations that were under pressure from exotic conifer invasions. This meant that attribution of the causal agent of vegetation change was vital for differentiating forest management activities (planting / harvesting) from the management operations and vegetation encroachment associated with invasive exotic conifers.

We investigated the period between 2000 and 2019 in this study, these years were chosen because the availability of Landsat images for New Zealand prior to 2000 is limited and because the invasive conifer control activities in our study area have only been undertaken at a large scale since around the year 2000.

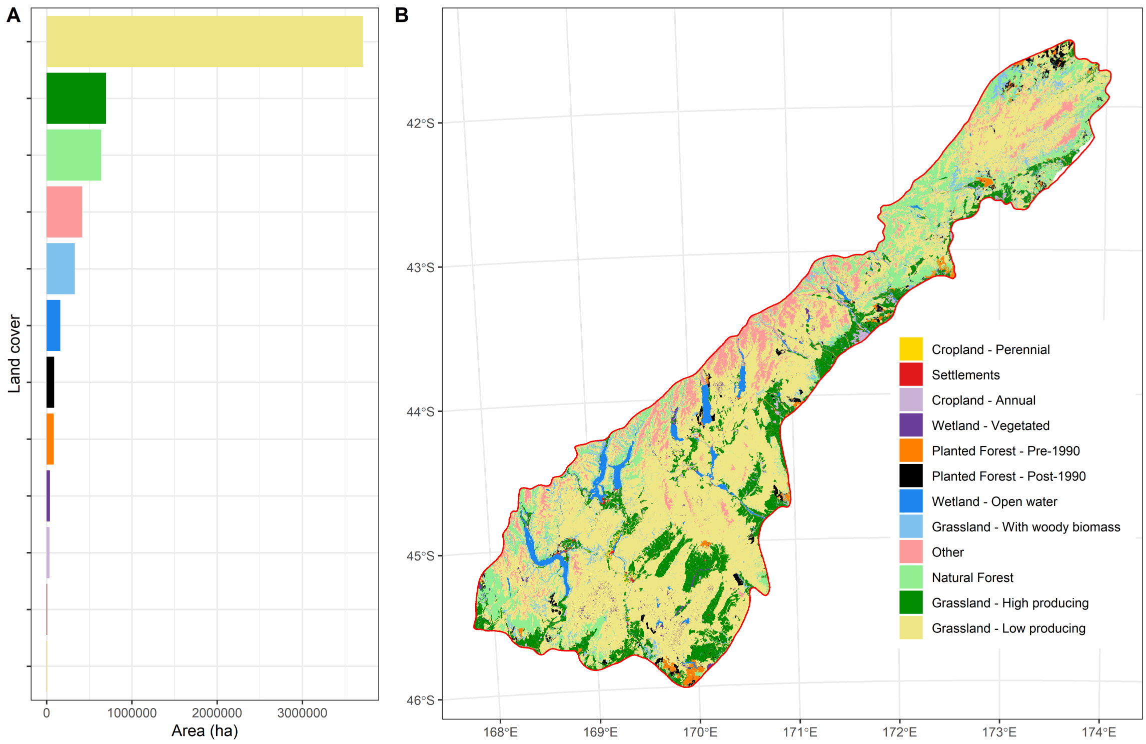

Fig. 6.4 The area of each LCDB land cover classification (Newsome et al., 2018) (A) and the spatial distribution of different land covers within the study area (B)

6.4.3 Overview

We have implemented a methodology designed to provide quantitative temporal estimates of land cover change associated with the encroachment and control of invasive conifers across the high-country of New Zealand's South Island. To aid the reader a schematic overview of the entire process has been provided (Figure 6.5) and a more detailed description of each aspect of the methodology is given in the following sections. The methodology followed was similar to that originally proposed by Kennedy et al. (2015) and can be split between pixel-level operations carried out in LT-GEE, patch-level analysis carried out in the R statistical computing language (R Core Team, 2018), and using the open source geospatial software GDAL (GDAL Development Team, 2016) and GRASS (GRASS Development Team, 2018). Pixel-level processes included selection of optimal LandTrendR settings, generating annual mosaics of spectral indices for segmentation and attribution, temporal segmentation of the spectral properties, production and stabilisation of stacks of tasselled-cap transformed Landsat imagery, and production of maps showing areas of vegetation loss or gain across the area of interest. Patch-level processes included patch definition, manual interpretation of the causal agents of identified changes, random forest modelling and accuracy assessment (Figure 6.5).

6.4.4 Landsat spectral properties

Spectral indices and transformations calculated from combinations of bands within Landsat imagery have a long history of being successfully used to extract meaningful information about land cover. We used the normalised burn ratio (NBR) to identify change segments. The NBR is a spectral index developed for Landsat data that uses the normalised difference between the near-infrared (NIR) and short-wave infrared (SWIR) bands in a similar manner to the formulation of the normalised difference vegetation index (NDVI). Since its initial development (García and Caselles, 1991) NBR has become widely accepted as the standard index to estimate forest disturbance severity, particularly for fire disturbance (Epting et al., 2005; Roy et al., 2006; Veraverbeke et al., 2010), and is used as a national operational tool for this purpose in the USA (Eidenshink et al., 2007).

To describe the spectral and temporal properties of the Landsat archive for the area of interest the tasselled-cap (TC) transformation was used. The TC transformation was developed to reduce the dimensionality of Landsat's optical spectral bands into three orthogonal indices that are easier to visualise and interpret (Pasquarella et al., 2016). The TC transformation emphasises data structures that represent the physical properties of vegetated terrestrial systems, these properties can be compared within and across scenes (Cohen and Spies, 1992; Crist and Kauth, 1986). The TC transformation

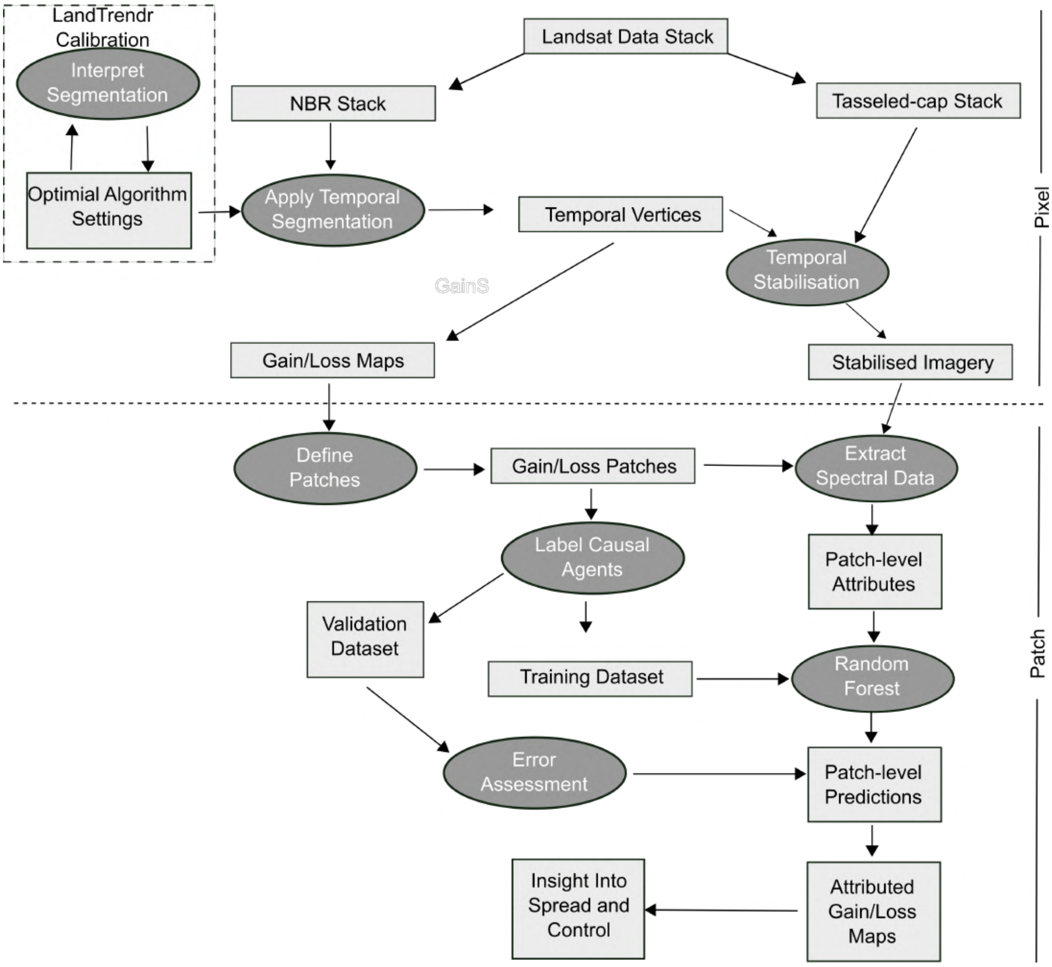

Fig. 6.5 Schematic of the change attribution modelling process. The top portion of the schematic occurs at the Landsat pixel grain, using LT-GEE to identify disturbances and stabilise time series tasselled-cap imagery. Based on temporal coherence and spatial adjacency, disturbance pixels are grouped into patches from which a variety of spectral attributes are summarised, and for which human interpreters label the agent causing the disturbance. These are combined within the Random Forest algorithm to predict change agents for all other patches in the map. These predictions can then be compared against a validation dataset to assess true error. This method is adapted from that originally developed in Kennedy et al. (2015).

reduces the Landsat spectral bands into tasselled cap brightness (TCB) which captures variation in overall reflectance, tasselled cap greenness (TCG) which captures variation in green vegetation, and tasselled cap wetness (TCW) which captures the interaction between moisture conditions and vegetation structure (Cohen and Spies, 1992; Crist and Kauth, 1986; Pasquarella et al., 2016). Calculation of the TC transformation for the image stack and fitting TC bands to the vertices identified using NBR were handled within LT-GEE. As multiple Landsat sensors were used to cover the entire time period a harmonisation of the spectral bands between different sensors (Roy et al., 2016) was also applied.

6.4.5 LandTrendR algorithm

For the Landsat scenes that intersect the study area we applied LandTrendR pre-processing, segmentation, disturbance, and growth mapping as described in (Kennedy et al., 2015, 2010, 2012) and implemented within LT-GEE (Kennedy et al., 2018a). The open source Java Script implementation of LandTrendR made available in GEE was used for all data acquisition, processing, and segmentation (https://emapr.github.io/LT-GEE/index.html) and following the methodology proposed by Kennedy et al. (2015).

The Landsat imagery for the study site were downloaded for the years between 2000 and 2019 within the late-summer season (January 1 to April 30). In total 2,079 images covering the study area were extracted from the Landsat archives between 1st January and 30th April for each year between 2000 and 2019 and used in this analysis. Imagery from Landsat 5,7, and 8 were included (Figure 6.6). These images were converted to a single annual medoid composite (Kennedy et al., 2015) that most closely represented the median late-summer vegetation conditions.

Atmospheric correction, normalisation, and cloud/shadow/snow masking (Zhu et al., 2015a) were applied to construct a clean image time series. The NBR was calculated for each image composite and LandTrendR temporal segmentation algorithms were then applied to the NBR time series, to identify breaks ("vertices") that separate time periods of consistent loss, gain, or stability within the spectral index trajectory (Kennedy et al., 2015, 2010). In a second phase of segmentation, the progression of

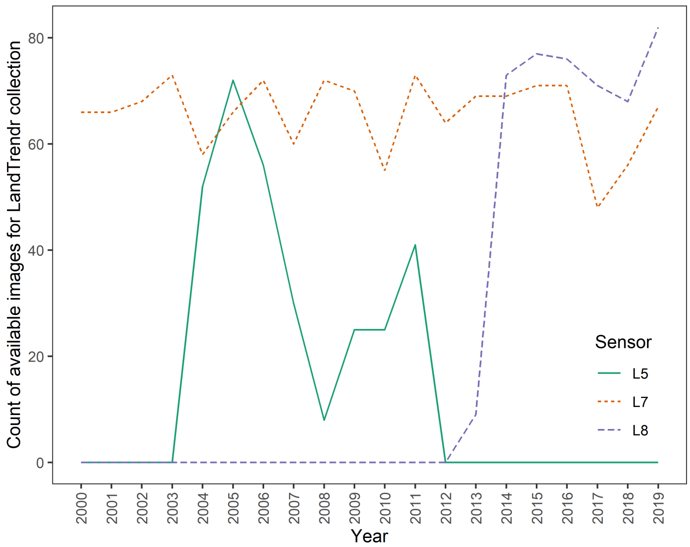

Fig. 6.6 The count of Landsat images for the study area included in the LandTrendR collection used in this study. Images were available from Landsat 8 (L8), Landsat 7 (L7), and Landsat 5 (L5) over the 19 year period.

spectral data between vertices is approximated with straight line fitting, resulting in segments that define periods of consistent temporal progression.

The LandTrendR algorithm was calibrated for our specific objectives of monitoring invasive conifer encroachment and management effect following the methods described in Liang et al. (2014); Shimizu et al. (2016). Simple random sampling without replacement was used to identify 50 calibration plots in each of the aggregated land cover classes of interest (strata) including planted forests, and at-risk low-producing grassland and shrubland (n=100). We then ran the LandTrendR algorithm with each combination of candidate parameters (Table 6.1).

The LandTrendR outputs were manually compared to a visual interpretation of time series imagery available through the TimeSync Legacy software (Cohen et al., 2010). TimeSync Legacy provides a means for extracting and plotting Landsat spectral trajectories from GEE and allows the user to visualise annual tasselled-cap transformed Landsat imagery to help interpret the cause of change. This was supplemented with high-resolution time series imagery available through Google Earth Pro. For each combination of parameters a score was calculated by summing the number of segment vertices in the NBR trajectories that were successfully captured by LandTrendR and matched the visual interpretation. The combination of parameters with the highest score was selected for use in the development of change maps. Once calibrated the LT-GEE algorithm appeared to provide reasonably realistic segmentation of the spectral trajectories of affected pixels in the calibration plots. For example, the plot shown in Figure 6.7 clearly shows invasion of a grassland area by exotic conifers. This is evident in the high-resolution time series images and is well represented by the NBR trajectory extracted from the annual Landsat image stack. Furthermore, the model fit accurately depicts the change in land use observed through the time series imagery stack.

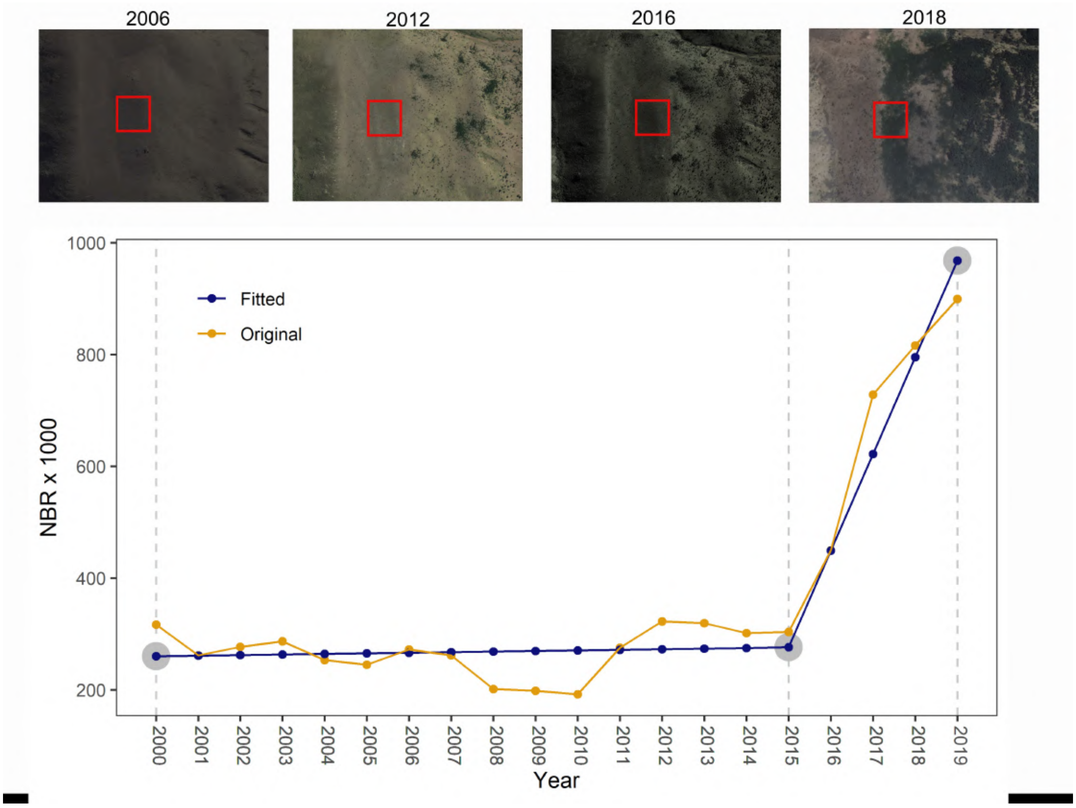

Fig. 6.7 An example of the spectral trajectory of a pixel invaded by exotic conifers. The high resolution imagery available in Google Earth and used for calibration and validation of the spectral segments detected by LandTrendR is also shown.

Table 6.1 LandTrender parameters tested during calibration. The values selected and used are in **bold**.

Parameter	**Description**	**Values tested**
Despike	An outlier will be removed if the proportional difference in NBR values between two adjacent points is less than this parameter	**0.9**, 1, 0.75
$pVal$	The entire trajectory is considered no-change, if the p value of F-statistic calculated from the best fitted trajectory is higher than $pVal$	**0.05**, 0.1, 0.2
$MaxSeg$	The maximum number of segments allowed in fitting	**4**, 5, 6
$recoveryThreshold$	The segment whose recovery rate is higher than $1/recoveryThreshold$ is not allowed	**0.25**, 0.5, 1
$vertexcountOvershoot$	The potential vertices are identified until the number of segments reached the number set by the sum of $MaxSeg$ and $vertexcountOvershoot$	0, **3**
$bestModelProportion$	A simpler model is chosen if its F-statistic exceeds $bestmodelProportion$	0.5, **0.75**, 1

Temporal segments that exhibited a decrease in NBR from onset to end of segment were considered a disturbance and those that increased were considered vegetation gain or encroachment. For each disturbance event in each pixel, the following attributes were outputted from LT-GEE: year of disturbance, duration of the segment, relative magnitude of change in NBR, and the rate of change in NBR. Occasionally, single pixels would have more than one disturbance event, and both events were noted but the change maps outputted from LT-GEE displayed the greatest vegetation loss and gain event respectively. This process was applied to all pixels in the study area resulting in the production of vegetation disturbance and gain maps that contained the spectral attributes of disturbance and vegetation gain for each pixel.

Prior to extraction from LT-GEE the pixel level vegetation disturbance and gain maps were grouped to provide contiguous patch-level homogeneous events that might represent invasive conifer control or encroachment within a segment. The pixel to patch conversion applied a set of filters available within LT-GEE. A separate set of filter parameters were applied for disturbance and for the gain maps developed (Table 6.2) following iterative testing and visualisation of the results within the LT-GEE interface. Critical parameters include the magnitude of the change in NBR, the duration of the observed change and the value of NBR prior to the onset of the segmentation. Even after extensive iterative testing of filter settings and comparison of outputs at a wide range of sites the selection of appropriate settings still required a value judgement on the best settings by the analyst. The phenomenon under study is relatively rare at a landscape scale and is highly variable. In particular, the spread rates of different conifer species in different environments ranges from slow incursion of one or two trees per year into a host environment as the result of long distance dispersal through to infill and blanket coverage of an entire grassland area through short distance dispersal with high propagule pressure. This variability means that selection of the most appropriate filter settings will always remain challenging and a source of uncertainty in any outputs produced.

There were substantial differences in the filter parameters selected for gain and disturbance to reflect the different vegetation changes (Table 6.2). The pre-segmentation value (Pre-value) selected was critical to reduce inclusion of false change and unwanted land covers such as land being managed for agriculture. The disturbance maps were restricted to areas with a pre-disturbance value of greater than 0.6 as this value was restricted to areas of dense vegetation such as mature plantation stands or well developed exotic conifer invasions that are often candidates for control activity. The gain map was restricted to areas with a pre-gain value of less than 0.4 as this was found to exclude many areas of immature plantations going through a process of maturation but included large areas of vulnerable grassland. These areas may have a history of disturbance and are particularly vulnerable to invasion from nearby plantations or scattered legacy trees in the landscape that can provide a seed source. Selection of the minimum patch size filter (mmu) is an important step in algorithm calibration. The mmu filter is designed to reduce small areas of spatial noise in the output maps. This was set to 11 meaning that the output was limited to areas of 11 contiguous pixels or more, this is approximately equivalent to 1 ha and so in this study we can not comment on the suitability of the technique to areas smaller than this. An alternative approach to algorithm calibration would be to not specify filtering parameters so that change detection is unlimited. This would inevitably include many areas of non-target forms of land-use change and areas where the changes detected were false. This would maximise sensitivity of the initial LT-GEE outputs to change, whilst increasing false positive results. It is possible that with good attribution modelling in subsequent processing steps these results can be refined to produce useful outputs. Although we did not follow the unfiltered approach this could be a suitable area for future iterations of this methodology.

Table 6.2 Patch-level settings for producing vegetation disturbance and gain maps.

Parameter	**Disturbance**	**Gain**
Year range	2000–2019	2000–2019
Magnitude	0.3	0.35
Duration (y)	<4	<6
Pre-value	0.6>	<0.4
mmu	11	11

6.4.6 Attribution of change and random forest modelling.

LandTrendR outputs showing vegetation gain and disturbance across the study area were used as initial candidates for areas invaded by exotic conifers or subject to invasive conifer control during the study period. These areas were considered base learners and subjected to secondary classification using random forest models to attribute the causal agent of the observed change. Patch-level change maps outputted from LT-GEE were segmented and polygonised using the i.segment and r.to.vector tools within GRASS GIS (GRASS Development Team, 2018) to provide a set of vectors showing candidate vegetation change patches. These were intersected with rasters detailing the spectral segments produced by LandTrendR and the stabilised TC transformed spectral data from the Landsat annual medoid (Flood, 2013) composites used for segmentation. The stabilised spectral data at the time of change detection (*start*), one year prior (*pre*), one year post detection (*post*), and at the end of each segment (*end*) for each patch along with the magnitude of change (δ) were calculated. These time steps were selected as it was hoped that they would provide useful insight into the spectral trajectories of the different land use changes. These spectral data constituted the feature space for random forest models that attempted to attribute the causal agent of change for a set of reference segments (Table 6.3).

A subset of the change polygons (n=400) were randomly selected without replacement for interpretation using TimeSync Legacy. These samples were augmented with a set of pre-existing interpretation plots (n=436) located randomly throughout the study area some of which intersected with the LT-GEE patches. Where a pre-existing interpretation plot intersected with the LT-GEE it was included in this analysis. A set of attribution agent class definitions were developed following an initial review of time series imagery (Table 6.4) and each of the selected change patches were classified accordingly by a human interpreter. The causal agents were collated into simpler

Table 6.3 Predictor variables used in random forest attribution modelling. The suffix used to identify the class of predictor variable is also provided (e.g. *TCW.pre* referred to the patch mean TCW prior to the start of an event and $NBR\delta$ referred to the change in patch mean NBR during the event).

Class	**Variable**	**Suffix**
Event	Patch spectral mean of NBR and TC band values during the year of detection of gain or loss event.	*start*
Pre-event	Patch spectral mean of NBR and TC band values one year prior to the detection of gain or loss event.	*pre*
Post-event	Patch spectral mean of NBR and TC band values one year post the detection of gain or loss event.	*post*
Trajectory	The change in patch spectral mean of NBR and TC over the duration of the change event.	δ
End-event	Patch spectral mean of NBR and TC band values at the end of the detected event period.	*end*

categories (Table 6.4) and these simplified categories were used as the response variables during random forest modelling. Separate random forest models were trained to predict the causal agent of the detected vegetation disturbance and gain patches using the stabilised spectral information for the segment as predictor variables (Table 6.3). Models were trained and fitted using the caret R package (Wing et al., 2018) and then used to predict the causal agent for the observed changes across the entire area of interest within the study area. The purpose of model development was to extrapolate the human interpreted change agent attribution from selected patches to the entirety of the initial segments. In this manner maps were created for the entire study area that could provide insight into the areas affected by invasive conifer encroachment or areas invaded by invasive conifers that had been subjected to control activity.

Table 6.4 Legend classifications for reference labelling.

Descriptive Name	Simplified	Type
0 - No change; a false positive	0	None
1 - Fire	1	Loss
2 - Herbicide control of invasive conifers	2	Loss
3 - Mechanical control of invasive conifers	2	Loss
4 - Forest Management: Harvesting or thinning	3	Loss
5 - Forest Management: Replanting	3	Gain
6 - Forest Management: Maturation	3	Gain
7 - New forest planting	3	Gain
8 - Invasive conifer spread	4	Gain
9 - Other vegetation encroachment	5	Gain
10 - Other vegetation control (e.g.gorse)	6	Loss
11 - Windthrow	1	Loss
12 - Insect or pathogen damage	1	Loss
13 - Riparian change	7	Both
14 - Agricultural activity - grazing / irrigation	0	Both

6.4.7 Validation

Model validation used comparison with human interpretation in the same manner as the model training data using TimeSync Legacy and Google Earth Pro imagery. A range of validation steps were implemented to validate various aspects of the change detection. To assess the initial change patches identified under each scenario a set of 100 randomly selected plots within the study area were used. High resolution time series imagery was used to assign each plot as either no-change, vegetation gain, or vegetation loss by a human interpreter. These interpretations were then compared to the LT-GEE change patches outputted for each scenario and used to quantify the proportion of matches, commission, and omission errors. The random forest models of change attribution were assessed through out-of-bag (OOB) errors and independent validation using a separate set of interpretation plots selected using simple random sampling from within the patch-level change maps. Although OOB error is thought to provide a robust assessment of error, our training dataset was relatively small, and was unlikely to represent patterns in the study landscape. For these reasons we chose to validate our predictions using a completely independent dataset of 50 patches selected at random from within each of the vegetation gain and disturbance maps (n=100). These were linked with the mapped predictions to create standard confusion matrices (Kennedy et al., 2015).

6.4.8 Mapping and summation

The random forest attribution models were then used to map disturbance and vegetation gain across the area of interest. These maps were used to identify the area affected within each year since 2000 to identify any trends in invasive conifer spread and control rates. The study area transects several invasive conifer management areas (ICMA) that are used by New Zealand government agencies to manage control activities. Within each ICMA the area of invasive conifer control and spread were summarised and investigated to provide operational outputs that might be useful for stakeholders.

6.4.9 Exploring Spectral Trajectories

To provide initial exploration of the spectral trajectory of various land uses within the study area a set of example pixels were selected (Table 6.5). The purpose of this exercise was to identify what trends might be present and to test whether LT-GEE might be useful in the context of monitoring invasive conifer spread and control through time. LT-GEE change vertices were fitted to estimate the year, type (gain or disturbance), and magnitude of vegetation change across New Zealand's South Island. Known areas of agricultural land use and water were excluded from the mapped area. Example pixels were selected from the area around the Craigieburn Invasive Conifer Management Area (CMA) defined by the New Zealand government agencies. Four pixels with distinctly different land use change patterns were identified and their spectral trajectories alongside the vertices associated with vegetation changes detected by LT-GEE were plotted (Figure 6.10). To provide a simple and readily available check that the spectral trajectories produced were logical and the changes identified were realistic the time series imagery available within Google Earth Pro was reviewed.

Table 6.5 Summary of the example pixels used to evaluate the spectral trajectory of various land use change within the study area.

Identifier	Land cover	Latitude	Longitude
1	Herbicide sprayed 2015	-43.16439727	171.7208508
2	Undisturbed Mountain beech	-43.16274344	171.68953179
3	Invaded 2009	-43.1733301	171.7700443
4	Harvested - replanted	-43.46209264	171.87833336

6.5 Results

6.5.1 The Landsat archive for New Zealand

From the beginning of image acquisition (1984) until 31 December 2018 there were a total of 24,555 images covering New Zealand's land surface. Of these images the majority (59%) were collected using the ETM, followed by the OLI (20%), TM (20%), and MSS (1%). These proportions differ substantially from those reported for Finland (Saarinen et al., 2018b) where there was a higher density of TM imagery leading to a greater temporal coverage throughout the late 1980s and 1990s. By contrast, the Landsat archive for New Zealand includes some substantial data gaps during these years (Figure 6.8). The majority of images covering New Zealand were acquired following the launch of ETM, with the improved coverage probably resulting from the new long-term systematic acquisition plan (Arvidson et al., 2001). Data density increased dramatically again with the launch and operational success of the latest asset (Landsat 8 - OLI) in early 2013. As these sensors operate together the rate of addition to the New Zealand archive is now at its highest rate (Figure 6.8). The day of year for image acquisition is of interest because both atmospheric and vegetation conditions vary through the year. An assessment of the day of year (DOY) acquisition of images containing less than 70 % cloud cover (Figure 6.8 inset) revealed that the quantity of images was slightly higher during the Southern Hemisphere summer periods. However, the variance between winter and summer acquisitions was not as marked as reported for other regions and this is probably due to the relatively uniformed cloud cover conditions in New Zealand throughout the year.

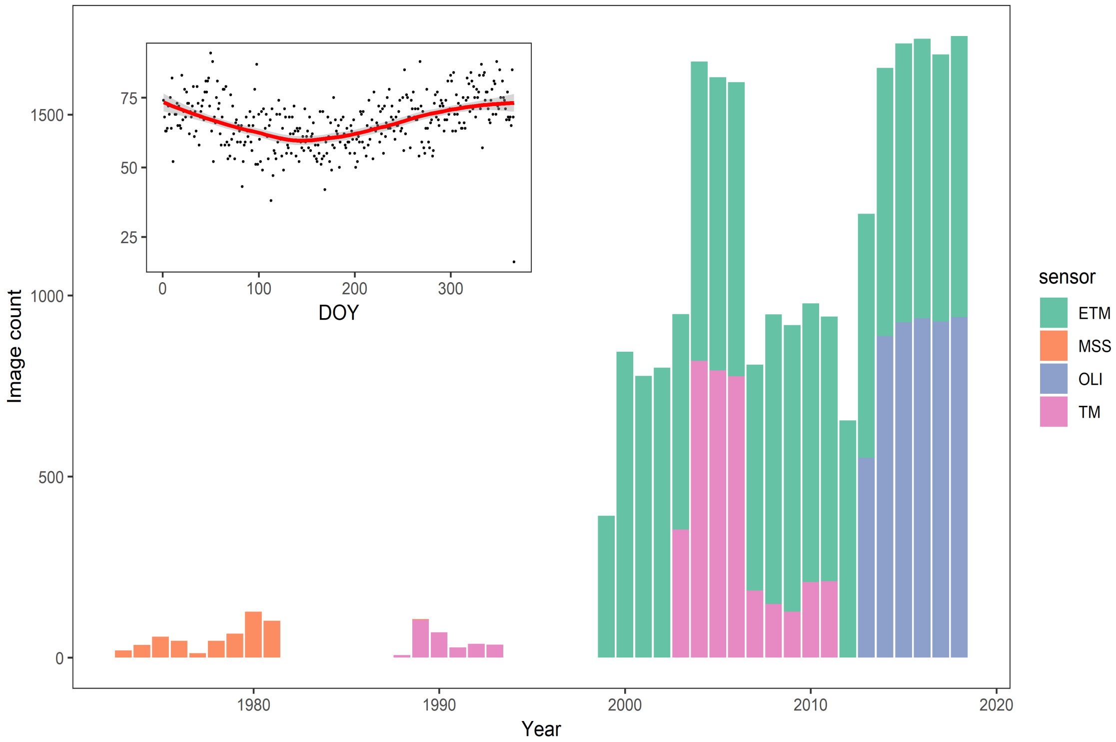

Fig. 6.8 Total number of Landsat images available for New Zealand summarised by acquisition year and sensor(ETM = Enhanced Thematic Mapper, MSS = Multispectral Scanner, OLI = Operational Land Imager, and TM = Thematic Mapper). The inset image shows the count of images available for each day of the year (DOY).

Mapping the density of images in the Landsat archive for New Zealand (Figure 6.9) provides detail on the likely coverage of imagery and availability of time series data from the various Landsat instruments. This analysis shows that all four instruments provide total coverage of the North and South Islands but the count of images varies considerably by sensor. The majority of images available are from the ETM that provides a uniform distribution of between 250 and 300 images for the scenes covering New Zealand's land area. This is mainly due to the long, and ongoing, operation of Landsat 7 (ETM). The next largest contribution of images comes from OLI which provides a more uniform distribution of suitable images across both islands with slightly higher amount across the North Island. There are substantially fewer images associated with TM and MSS sensor.

The review of the Landsat archive for New Zealand has revealed that although there is good coverage for the majority of both the North and South Islands there are also substantial gaps in the continuity of imagery. The image time series is dense from the present time back to the year 2000. Prior to the year 2000 there are periods with very limited, or no suitable image availability. As a result, the scope and the findings of this analysis were limited to imagery from 2000 onward. This does not significantly reduce the applicability of this study as the majority of invasive conifer management activities have been deployed since the year 2000. As such, the archive clearly provides a valuable means for temporal segmentation of land use and vegetation patterns that should enable the detection of invasive conifer spread to new areas as well as vegetation changes associated with control methods. Invasive conifer control rates have increased in more recent years and as a result the temporal pattern of image availability may limit our ability to monitor post-control recovery either to an alternative land cover (e.g. grass land of forest dominated by indigenous species) or back into invasive conifers.

6.5.2 Initial Exploratory Results

The results of the initial comparison of the four example pixels indicated that LT-GEE was useful for accurately identifying change within the study area that was consistent with observed land cover changes. Example pixel one (Table 6.5) covers an area where

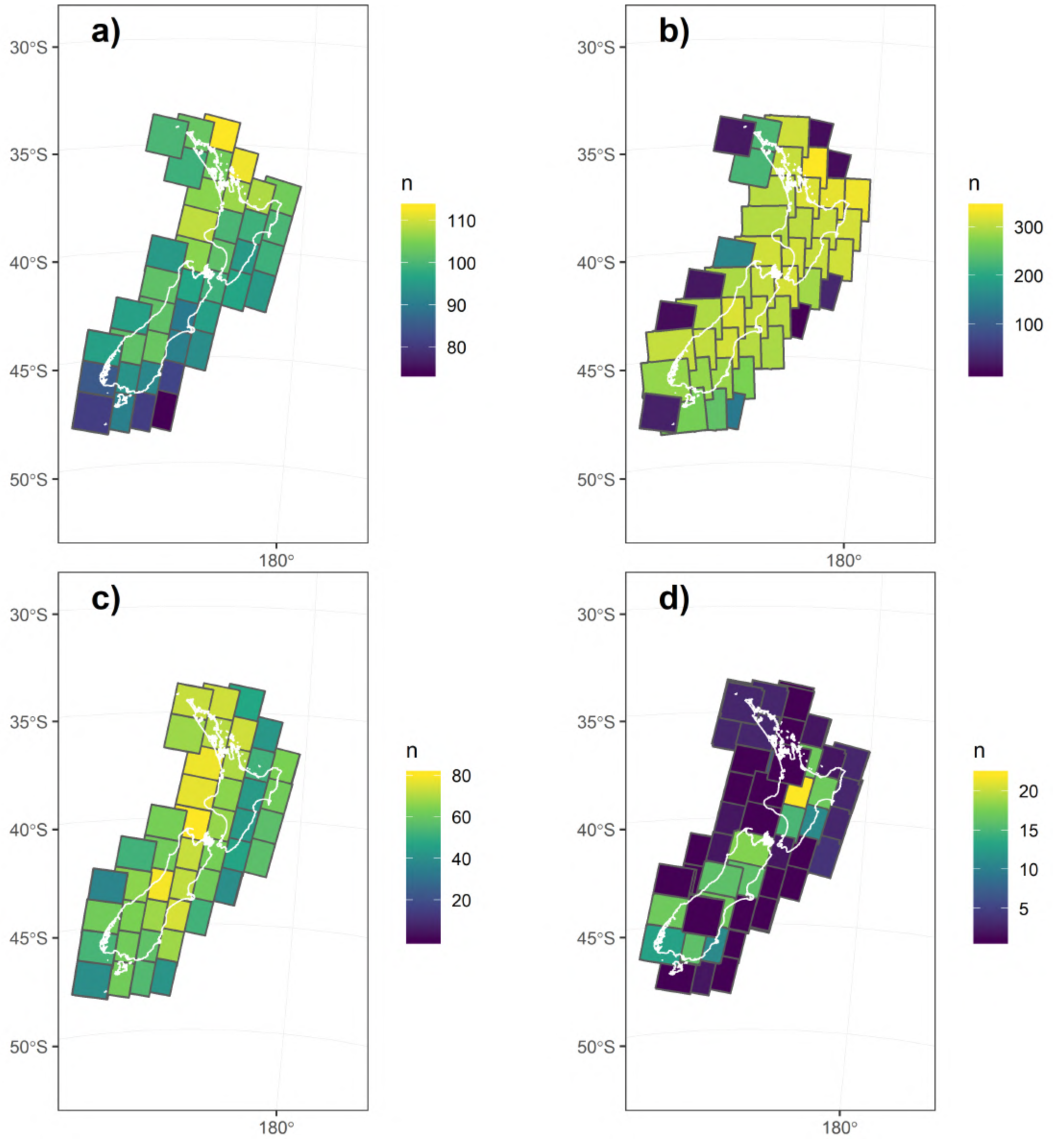

Fig. 6.9 The count (n) of images with less than 70% cloud cover over New Zealand in the USGS Landsat archive up to Dec 31st 2018 for a) Operational Land Imager, b) Enhanced Thematic Mapper, c) Thematic Mapper, and d) Multispectral Scanner.

an invasive conifer invasion was already present at the start of the Landsat time series stack (year = 2000). The spectral trajectory shows a steady and gradual increase in NBR as the invasive conifers get larger and new trees are recruited either from within or outside of the invasion (Figure 6.10 a and b). There was a management activity to control the invasion that was detected by LT-GEE in 2013. This was probably an aerially applied herbicide treatment to control the dense infestation. This was followed by a period of rapid decline in NBR, followed by a stabilisation of the index which then exhibits steady decline through to the end of the observation period. A review of the historic imagery available through Google Earth supports the results and interpretation. The Google Earth Pro imagery clearly shows a dense infestation of conifers which increases in greenness and density until dramatic discolouration associated with herbicide application becomes evident. This is followed by some years where the trees appear red as the dead needles remain on the trees before reverting to a grey colour indicating that the needles have been dropped, the trees in the invasion appear to be dead, and the invasive conifer stand appears to be in a state of decline. These results indicate that the LT-GEE is capable of identifying areas dominated by invasive conifers that have been controlled using herbicide application.

Example pixel two is located in undisturbed natural forest within the CMA with an overstorey dominated by Mountain beech (*Nothofagus solandri var. cliffortioides* Hook F.). No changes were detected in the spectral trajectory of this pixel between 2000 and 2018 (Figure 6.10 c and d). This is consistent with plotting and observation of several spectral indices that remained very stable throughout this period. Examination of the available time series reference imagery also confirmed that there was no disturbance in the forest during this period.

Example pixel three is located in a high-altitude area that has gradually been invaded by exotic conifers since the beginning of the study periods. The spectral trajectory of NBR shows a relatively minor increase between 2000 and 2007, a steeper increase between 2007 and 2012, and a somewhat more gradual increase from 2012 through to 2017 (Figure 6.10 e and f). The simplified model provided by LT-GEE segmented the spectral trajectory in this manner and indicated and detected the greatest vegetation gain in the year 2009. A review of the available imagery supports the conclusion that this trajectory is indicative of the colonisation of this area by exotic conifers during the study period. The results from this initial exploration suggest that the algorithm is sensitive to invasions by exotic conifers in this environment and is capable of defining the year when changes that have occurred. This was deemed to be strong evidence that LT-GEE was an appropriate tool for use in this research.

The spectral trajectory of a plantation forest area is represented by example pixel four (Figure 6.11). All available Google Earth reference images (Figure 6.11 b) are shown alongside the spectral trajectory of the example pixel for both NBR (Figure 6.11 a) and TCB (Figure 6.11 c). The reference images show the stand recently harvested in 2004, replanted in 2007, with closed canopy in 2014, and fully mature in 2016. This land cover history of the pixel is clearly reflected in the NBR pattern and the vertices identified using LT-GEE. At the start of the time series stack the NBR value is very high (ca. 0.9) until 2002, the harvesting event is reflected in a significant decrease in the NBR value down to a nadir of 0.15. The NBR then increased rapidly as the stand is replanted and returns to pre-harvest levels by 2007 as the new crop reaches maturity at which point NBR stabilises for the remainder of the study period. The TCB value also very clearly reflects the harvesting event in 2003 with the increased brightness of the underlying soil clearly evident as a substantial spike in TCB. Example pixel four clearly shows the capability of the spectral trajectories available from Landsat via LT-GEE to monitor forest changes associated with management activities.

The initial data exploration of the example pixels reported on here shows that the Landsat archive contains substantial information for the monitoring of both abrupt and gradual changes in vegetation cover within the study area. These include changes associated with invasive conifer spread and control measures.

LT-GEE provides several outputs that can be useful for monitoring invasive conifer spread and management. These include maps of disturbance and vegetation encroachment on areas previously occupied by alternative land uses. Initial maps of primary

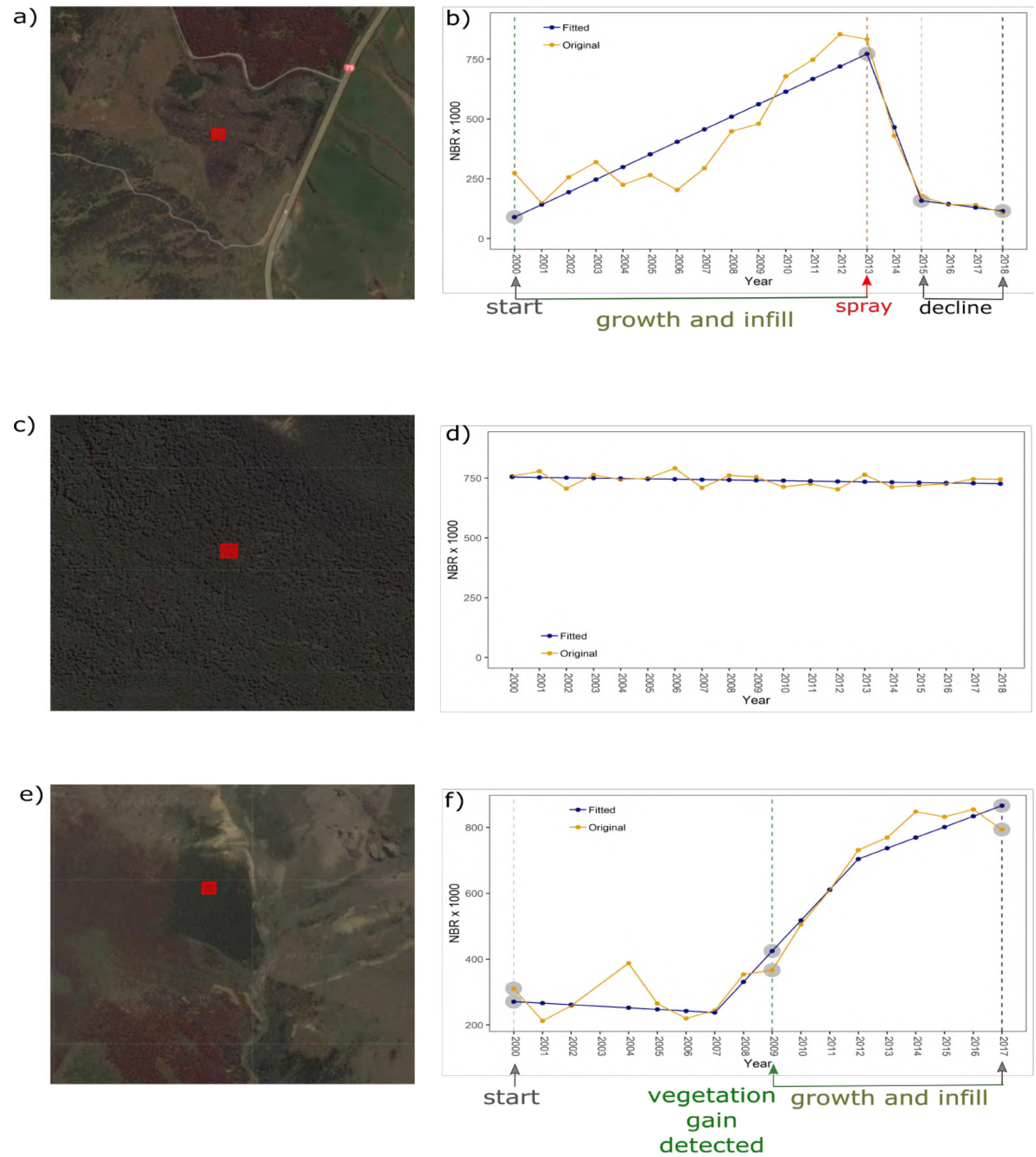

Fig. 6.10 The observed (Original) and modelled (Fitted) spectral trajectories of the Normalised Burn Ratio (NBR) and most recent Google Earth reference images for for example pixels 1 (a and b), 2 (c and d), and 3 (e and f). Filled grey circles indicate changes identified by LandTrendR.

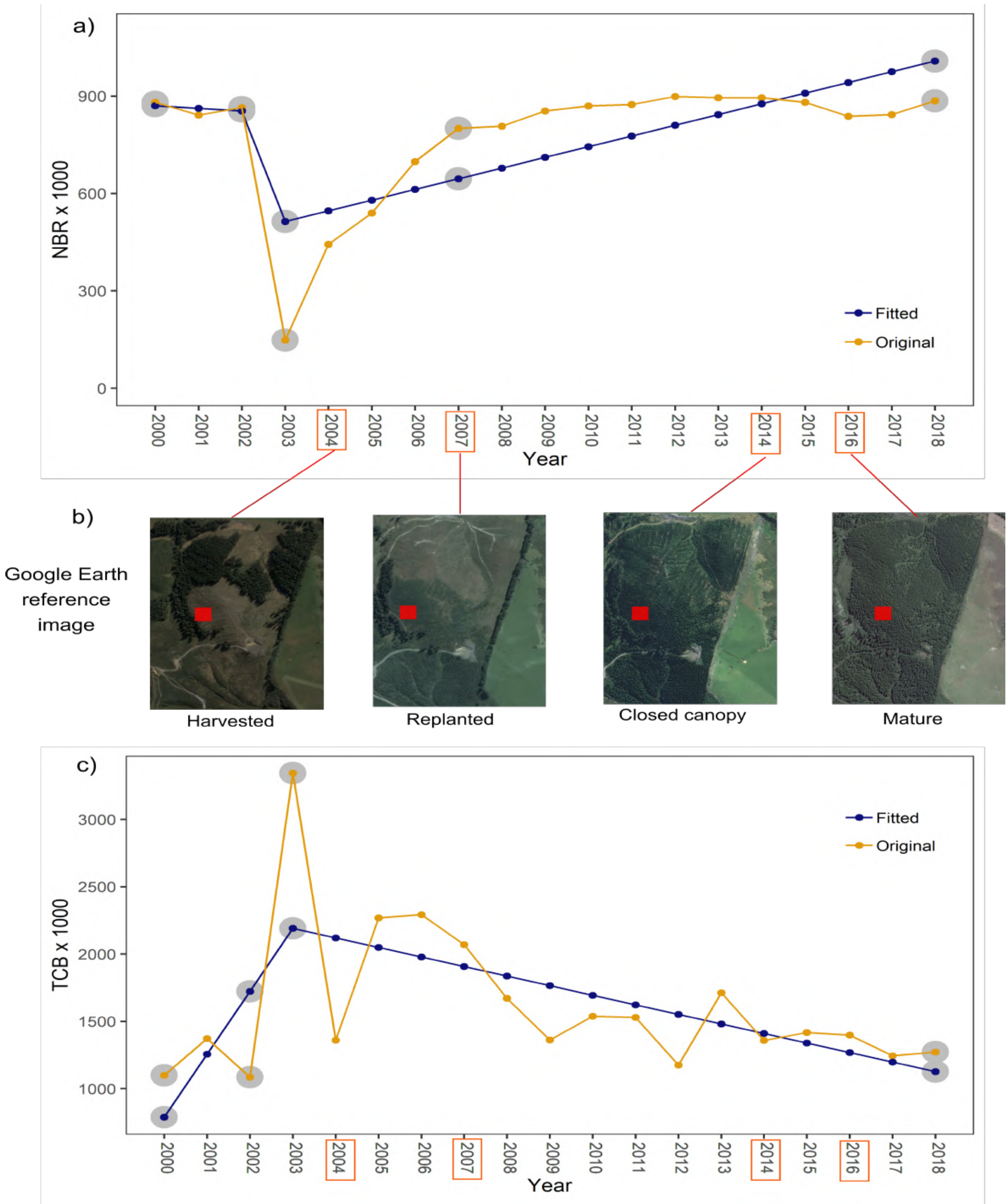

Fig. 6.11 The observed (Original) and modelled (Fitted) spectral trajectories of the Normalised Burn Ratio (NBR) (a) and taselled-cap brightness (TCB) for an example pixel in a managed plantation forest. Filled grey circles indicate changes identified by LandTrendR. A time-series of high-resolution satellite imagery showing a range of management activities (b) is also shown.

disturbance in CMA are included here (Figure 6.12). Maps showing the year of detection (Figure 6.12 B) and duration of disturbance (Figure 6.12 C) have been included here. An initial review of these maps indicates that they accurately depict invasive conifer control in certain parts of the study area.

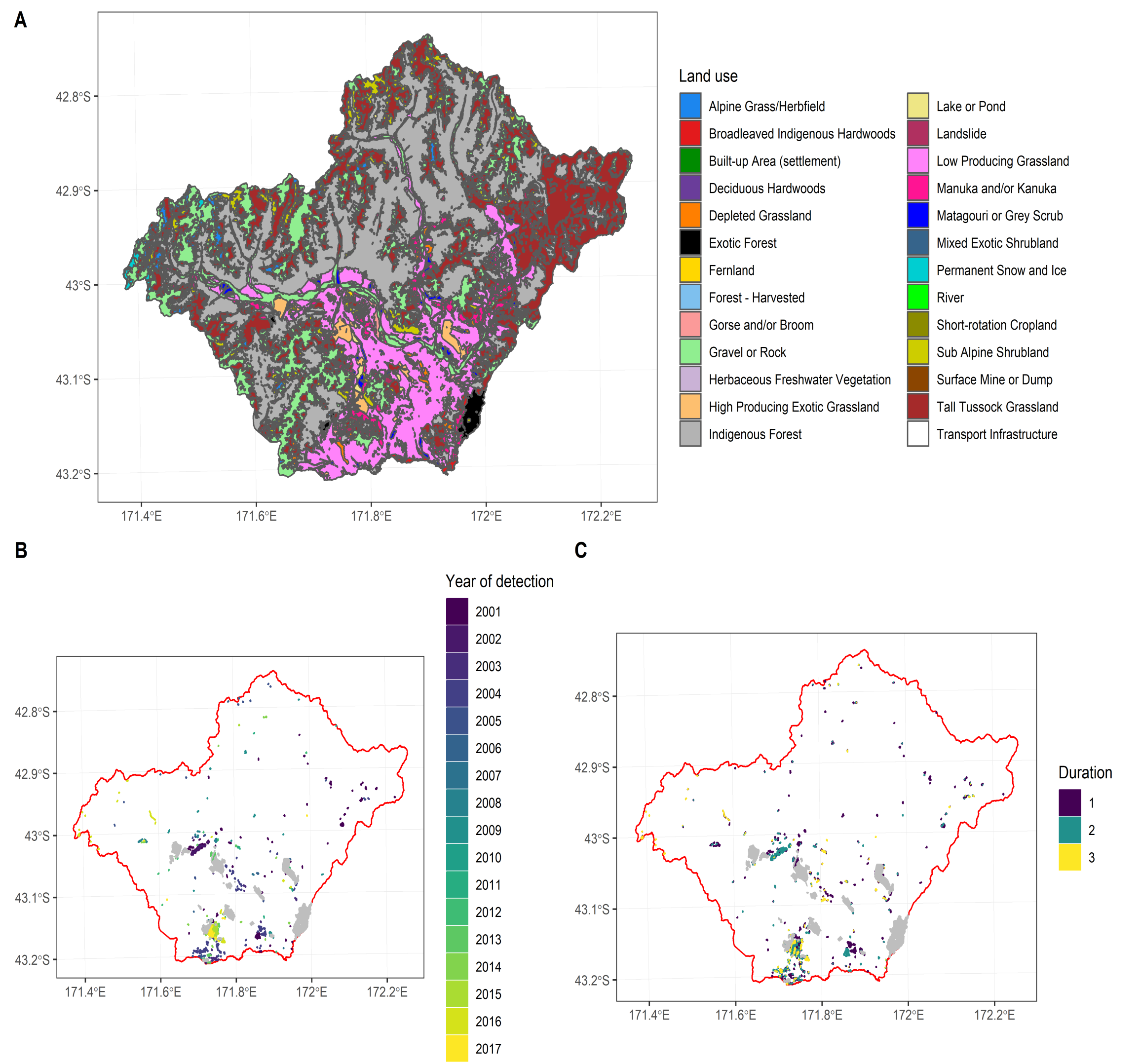

Fig. 6.12 The land use classifications for the Craigiburn Management Area from the LCDB 4.2 classification (A) and primary disturbance maps showing the year of detection (B) and the duration of disturbance (C) for the same area. Note that in B and C the areas classified as planted in exotic forest or containing high producing grassland or annual crops are masked and appear grey.

6.5.3 LandTrendR outputs and change detection

Following the promising results of the initial data explorations the large-scale case study described in the methods section was fully implemented. The subsequent sections summarise the study findings. In total 54,413 patches were produced with 38,063 representing vegetation disturbance and 16,350 representing vegetation gain (encroachment).

6.5.4 Change interpretations

Of the total 832 patches interpreted, roughly half (421) (Table 6.6) showed changes associated with forest management activity. The next largest amount was false change including that caused by the inception of agricultural irrigation or grazing on low-productivity grasslands to expand agricultural activity in the study area that could not be filtered out due to inaccuracies in the LCDB. Classes relating to the control (class 2) and encroachment (class 4) of invasive conifers were represented by 61 and 50 patches respectively. Spread and control of other vegetation types (notably *Ulex europaeus*) were also well represented in the interpretation patches.

Table 6.6 Summary of manual interpretation labels assigned to change classes.

Simplified Class	Count
0 - no change including false change (grazing)	211
1 - fire	0
2 - Invasive conifer control	61
3 - forest management	421
4 - invasive conifer encroachment	50
5 - other vegetation encroachment	55
6 - other vegetation control	28
7 - riparian changes (flooding / stream migration)	9

Table 6.7 Confusion matrix for out-of-bag accuracy estimates for change attribution class for (a) vegetation gain and (b) vegetation disturbance patches. Numbers in each cell correspond to the count of patches in that category. Diagonal cells (shaded) are correct calls; off-diagonal cells are errors. User's Accuracy (UA) and Producer's Accuracy (PA) are also shown with the overall accuracy displayed in bold font in the bottom corner.

(a) Vegetation gain

Class	0	3	4	5	PA
0	98	3	2	1	0.94
3	6	59	1	0	0.89
4	7	5	4	3	0.21
5	14	2	2	5	0.22
UA	0.77	0.86	0.44	0.56	**0.78**

(b) Vegetation disturbance

Class	0	2	3	6	PA
0	17	9	12	1	0.44
2	6	20	11	4	0.49
3	6	6	221	1	0.94
6	6	12	3	1	0.05
UA	0.49	0.43	0.89	0.14	**0.71**

6.5.5 Random forest attribution modelling

The random forest attribution models for vegetation gain and vegetation disturbance patches showed moderate overall accuracy with OOB estimates of 78% and 71% respectively. The most accurately classified change type in both models were those associate with forest management activities (Simplified class = 3) with the highest user's and producer's accuracy rates (Table 6.7). The random forest model for vegetation gain (Table 6.7 (a)) showed that there was significant confusion for change caused by invasive conifer encroachment (Simplified class = 4; User's accuracy = 0.44, Producer's accuracy = 0.21). Several patches were misclassified as either other vegetation encroachment (Simplified class = 5) or false change including grazing (Simplified class = 0). The OOB results for the random forest model associated with vegetation disturbance (Table 6.7 (b)) suggest that change associated with invasive conifer control (Simplified class = 2) was somewhat more accurate (User's accuracy = 0.43, Producer's accuracy = 0.49) suggesting that the parameterisation of models for both gain and disturbance may produce moderate accuracy results for this land cover change type.

Within random forest models the relative importance of predictor variables can be investigated by assessing the change in accuracy when a given variable is excluded.

Variables with higher importance impart a greater accuracy reduction in their absence and this is quantified through the "gini" coefficient (Breiman, 2001) (Table 6.8). For the vegetation gain random forest model developed here the most important predictors were the TCB value at the end of a gain segment ($TCB.end$) and the change in the TCB value over the duration of a gain segment (TCBδ). This was followed by the TCW change over the duration of a gain segment (TCWδ) and at the end of a gain segment $TCW.end$ (Table 6.8). For the vegetation disturbance random forest model the most important predictor for change attribution was the change in NBR during the duration of the disturbance segment (NBRδ) closely followed by the TCB value for the year immediately prior to the onset of the vegetation disturbance segment ($TCB.prechange$).

Table 6.8 Variable importance (Mean decrease in Gini) for all of the spectral predictors used in the gain and loss random forest models. Variable name definition is provided in Table 6.3

Variable	Gain	Loss
$NBR.\delta$	4.6	12.8
$NBR.start$	3.6	12.3
$TCB.start$	7	6.1
$TCG.start$	5.5	5.7
$TCW.start$	3.9	5.1
$TCB.end$	17.8	7.1
$TCG.end$	4.3	5.2
$TCW.end$	10.2	6.9
$TCB.prechange$	5.5	15.2
$TCG.prechange$	4.4	9.1
$TCW.prechange$	4.5	18.6
$NBR.prechange$	3.89	10.9
$TCB.postchange$	8.8	6.5
$TCG.postchange$	6.2	5.1
$TCW.postchange$	4.1	5.9
$NBR.postchange$	3.9	4
TCBδ	16.7	4.2
TCGδ	3.2	4.8
TCWδ	7.3	4.1

Table 6.9 Confusion matrix for independent accuracy estimates comparing model predictions to blind validation for change attribution class for (a) vegetation gain and (b) vegetation disturbance patches. Numbers in each cell correspond to the count of patches in that category. Diagonal cells (shaded) are correct calls; off-diagonal cells are errors. User's Accuracy (UA) and Producer's Accuracy (PA) are also shown with the overall accuracy displayed in bold font in the bottom left corner. Class definitions are provided in Table 6.4.

(a) Vegetation gain

Class	0	3	4	5	PA
0	27	0	3	1	0.87
3	0	11	1	0	0.92
4	0	0	5	1	0.83
5	0	0	1	0	0.00
UA	1.00	1.00	0.50	0.00	**0.86**

(b) Vegetation disturbance

Class	0	2	3	6	PA
0	10	3	1	0	0.71
2	1	7	1	0	0.78
3	0	0	25	0	1.00
6	1	0	0	1	0.50
UA	0.83	0.70	0.93	1.00	**0.70**

Independent verification of the accuracy of the attribution maps showed that the overall accuracy was 86% for the gain maps and 70% for the disturbance patches (Table 6.9). With the small sample size, the validation must be treated with some caution as rarer change types were not well represented. The independent validation showed similar levels of accuracy to the OOB accuracy assessment (Table 6.7). The most common change classes of forest management (3) and false change (0) were well represented in the validation sample. Prediction of change associated with forest management showed high accuracy for both gain (Producer's accuracy = 0.92, User's accuracy = 1.00) and disturbance patches (Producer's accuracy = 0.71, User's accuracy = 0.83). The change classes critical to this study related to invasive conifer spread (4) and control (2) showed only moderate accuracy. For the vegetation gain model, the attribution accuracy for invasive conifer spread was 0.83 and 0.5 for Producer's and User's accuracy respectively. Meanwhile, for vegetation disturbance patches the attribution accuracy for invasive conifer control was 0.78 and 0.7 for Producer's and User's accuracy respectively.

The attribution model was used to provide an estimate of areas that have been subjected to invasive conifer spread and control. Model outputs can be configured to show either the attribution class from each model or the probability of each attribution class. Both should be useful to managers as they can choose to either visualise the most likely change agent or they can visualise the likelihood of each change type and assess the confidence level they are most comfortable with for their intended application. Both map types were produced and reviewed to provide further insight into model performance.

With such a large study area global maps of invasive conifer control and encroachment provide limited insight. Instead we present localised maps of model outputs overlain onto recent high-resolution satellite imagery to aid model evaluation. In the vicinity of the township of Queenstown in Otago (Figure 6.13) there are substantial areas where exotic conifers spreading from commercial *Pseudotsuga menziesii* plantations to higher altitude areas have been controlled in recent years through herbicide spraying. In this example, many of these areas have been accurately detected and attributed (Figure 6.13 A). A minority of areas where it appears from the satellite imagery that herbicide has been applied (Figure 6.13 B) are not correctly identified (omission). Both omission examples in Figure 6.13 were identified as vegetation loss areas by the LT-GEE algorithm but then attributed to forest management activity. Invasive conifer control was the second most probable attribution class with a likelihood only slightly below the vote winning class.

A second example (Figure 6.14) shows identified invasive conifer control areas in the area around Craigieburn Forest Park which is a focus of control activities following extensive conifer plantings in the early 20th century. In this region there is evidence for correct attribution of herbicide control of both dense (Figure 6.14 A) and sparse (Figure 6.14 B) invasive conifer infestations. An area formerly covered with invasive conifers and subsequently mechanically cleared and converted to grazing is also evident

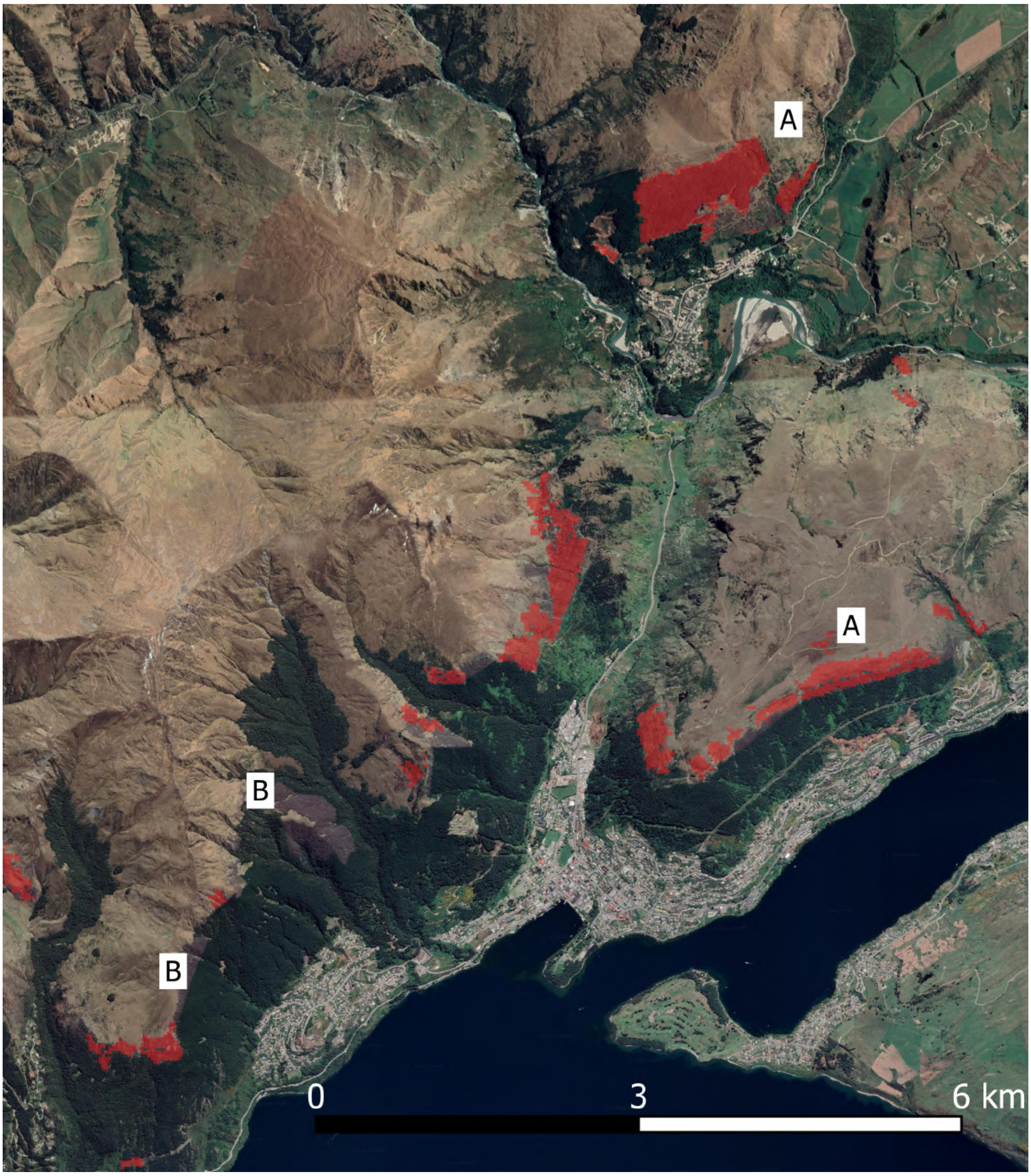

Fig. 6.13 Detailed map showing the model output in the vicinity of Queenstown, Otago with change areas attributed as invasive conifer control shown in red overlain onto recent high-resolution satellite imagery provided by Google. Areas where exotic conifer invasions have been herbicide treated have been correctly identified in most cases (marked A) but not others (marked B).

(Figure 6.14 C). It is also notable that smaller areas of invasive conifers treated with herbicide have not been correctly identified.

To support the national programme of invasive conifer monitoring and control, surfaces of historic control and spread can be summarised according to spatial data related to ICMA. This can provide useful information on the efficacy of control efforts and invasive conifer spread that could help better allocate resources into areas with the greatest demand or where control can add most value. An example of this type of output is provided here (Figure 6.15). This summary suggests that there has been significant variance in invasive conifer control in between management areas ranging from 2,262.4 ha in the Marlborough region to just 10.17 ha in the Nelson Lakes region. It is notable that areas where there have been significant invasive conifer control campaigns (e.g. Mackenzie, Arthurs Pass, and Queenstown) all show substantial areas of control. These values would likely be very different to those published by government agencies; this is probably due to both model error and the insensitivity of the approach to the control of scattered invasive conifers which are often subject to chainsaw control. This summary is meant as an illustration of the application of the modelling approach across an expansive area.

6.6 Discussion

An initial methodology has been presented that can be used to monitor historic exotic conifer invasions and their control across a large and varied study area for the period 2000 - 2019. This methodology makes use of the time series change detection algorithm LT-GEE to identify areas of vegetation loss and gain. Random forest modelling was then used to attribute the causal agent of the changes identified through LT-GEE. This was achieved by modelling change agents identified by a human interpreter using the stabilised spectral trajectory of segments extracted from LT-GEE. The attribution

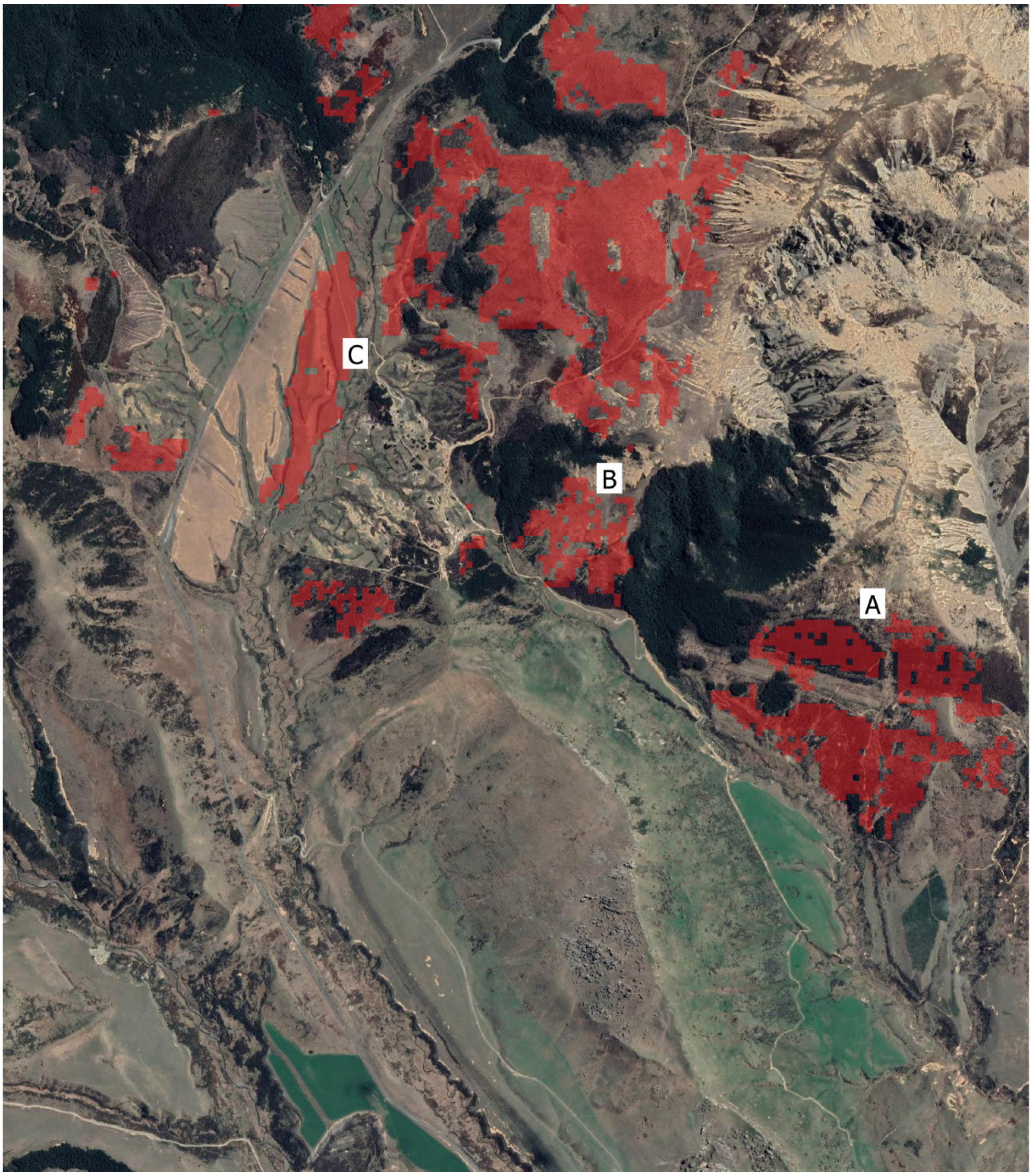

Fig. 6.14 Detailed map showing the model output in the vicinity of Craigieburn Forest Park, Canterbury with change areas attributed as invasive conifer control shown in red overlain onto recent high-resolution satellite imagery provided by Google. Areas where dense areas of exotic conifer invasions have been herbicide treated have been correctly identified (marked A), areas with scattered invasive conifers subject to herbicide control, (marked B), and areas where conifer infested areas have been mechanically cleared and converted to animal grazing (marked C).

Management Unit	Area (ha)
Amuri	2211.57
Arthurs Pass	1519.02
C.E. Southland	97.83
Central Otago	2182.50
Kakanui	779.85
Mackenzie	2151.18
Marlborough	2262.42
Nelson Lakes	10.17
Northern Southland	629.01
Plains + B. Penn.	205.83
Queenstown	1578.06
Wanaka	1665.99

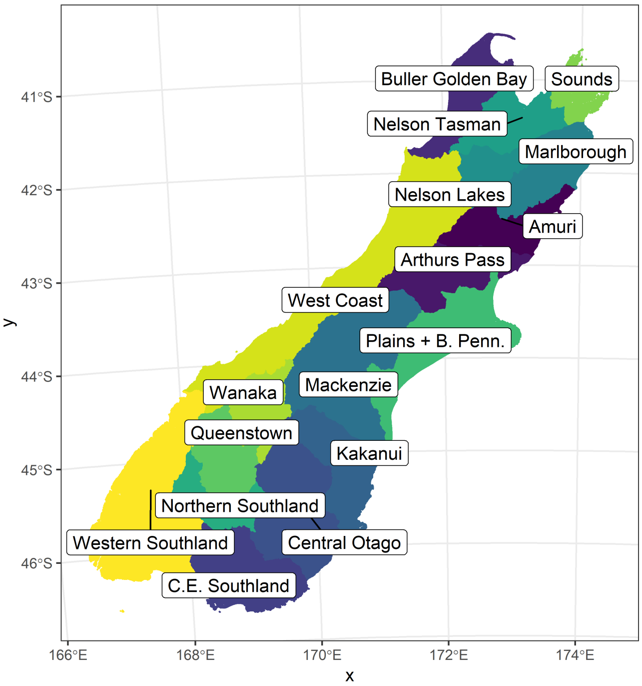

Fig. 6.15 Indicative areas of invasive conifer control in the invasive conifer management areas (ICMA) within the national programme. Areas quoted represent a sum of areas controlled since 2000 and a map of management areas is provided as a reference to the reader.

models developed had moderate accuracy and could be used to extrapolate the human interpreted change agents to all land use change patches within the study area. Maps showing expansion of conifer invasions and control activities between 2000 - 2019 were produced and validated using an independent dataset of change interpretations. This validation showed that the maps produced had moderate accuracy. The maps of invasive conifer control and spread were broadly consistent with observed landscape scale changes that could be derived through reviewing time series imagery. These maps could be summarised across the study area to provide information that is useful for stakeholders.

Through this case study we sought to address a series of five operationally relevant research questions that were specified in the paper introduction. Based on the evidence that we have presented it is clear that the LT-GEE algorithm approach can detect changes associated with both invasive conifer spread and control activities through time series analysis of the Landsat archive. We believe that LT-GEE is a good choice for our use case. This is because the high levels of cloud-cover in New Zealand for most of the year mean that an algorithm based on a single annual mosaic is more suitable than approaches that use the variability of the entire time series stack for continuous change detection.

Despite fastidious efforts to accurately calibrate the algorithm to reduce false positive and false negative samples, independent validation showed that a significant amount of both of these error types were present in the segmented datasets. This is unsurprising as LT-GEE is designed to detect all land use changes within a study period. An alternative approach worthy of further research would include a much less rigorous filtering of the pixel-level trajectories made available for attribution modelling. This would increase the sensitivity of the LT-GEE outputs to landscape changes and, with an appropriate interpretation dataset, the causal agent of these changes could be accurately modelled using an approach similar to the one presented here.

We have successfully produced attribution models that can identify the causal agent of land use change based on the spectral trajectories of segments through the Landsat time series. Independent validation showed that these models had moderate accuracy and there was commonly inter-class confusion particularly for the less common change types. Change types that were very distinctive and well represented in the interpretation dataset (such as forest management activities) were very accurately attributed in the random forest models. Change types that were less common and less distinct from other classes were less accurately represented. Unfortunately, this included both the control and expansion of conifer invasions in the study area. There was significant confusion between areas of conifer invasions and their control with other weed invasions and their control. This result was expected as differentiating between these classes was challenging for the human interpreters. Some weed species such as *Ulex europaeus* within the study area are quite distinct from conifers during flowering but depending on the date of the Landsat medoid used for a given year this may not be useful for differentiation. Further refinement of the methods and the attribution dataset could improve the confusion caused by these edge cases and improve model performance. Nevertheless, even with some degree of confusion between classes the maps of invasive conifer control and conifer invasions could be valuable to land managers with specialist knowledge of an area of interest who can better interpret changes in vegetation patterns identified when viewed within a GIS. It should also be noted that the probability of class membership can be outputted from the random forest model and can be useful when observing trends to assess the impact of a given management activity.

Our methodology can clearly be used to recreate the historical patterns of vegetation change within the study area. Accepting reasonable error rates our methods can also be used to provide a detailed history of invasive conifer encroachment into low-producing grassland and shrubland areas and invasive conifer control activities. This history can be recreated back to the year 2000 at which point the Landsat archive for the South Island of New Zealand is too sparse to follow this approach. Our methodology focused on the vegetation disturbance or gain with the greatest magnitude within the study period to create the initial segmentation of the time series stack. Land managers would likely be very interested in the subsequent spectral trajectory of a given segment which should provide useful information on subsequent land use changes. In this manner we should be able to provide insight into the efficacy of control activities. For example, when an initial vegetation disturbance was classified as invasive conifer control and subsequent events were classified as invasive conifer encroachment, this would indicate that a management activity had not been successful; further, and possibly different, management interventions were required at the site. To some extent our methodology can already provide this information for some areas but relatively minor adjustments to the algorithm settings could make it more likely that this type of scenario could be accurately modelled. This could provide a substantial improvement to help better inform policy development and to better inform allocation of management resources.

We have attempted to present a robust estimate of the errors that might arise when using this methodology so that we can comment on whether the accuracy of the results produced is adequate to meet the needs of stakeholders. In our methodology errors are introduced at several stages including through the selection of LT-GEE settings, attribution model misspecification, and the human interpretation of sample plots. Although we diligently attempted to limit the errors that would be introduced through the first two of these error sources, errors of this type were inevitably present. In general, it would probably be advantageous for land managers to have more false positive than false negative segments identified from LT-GEE to reduce the probability of invasive conifer spread or management events being missed. However, the inclusion of too many false positive events could cause stakeholders to lose confidence in the results provided, leading to limited uptake and a lack of trust in the results provided. Accuracy statistics are useful for expressing the expected error rates and these should be communicated to stakeholders and should travel with the data products produced from work of this type. Our models were only moderately accurate but have comparable accuracy levels to other studies on similar topics (Hudak et al., 2013; Kennedy et al., 2015; Liang et al., 2014) and should be sufficiently accurate for stakeholders to use with the relevant caution. In addition to the accuracy metrics from the independent validation the probability classes extracted from random forests can also be presented and can be used by stakeholders to select a level of confidence that they are comfortable with. In our study the errors caused by mis-attribution by the human interpreter are unknown and cannot be quantified. Despite the use of best practice methods for sample selection (Olofsson et al., 2014), and robust interpretation procedures within standardised software, interpretation errors for various segments will inevitably be present. These will be worse for sample plots where the high-resolution imagery used for interpretation is sparse, due to cloud cover, or unavailable. Independent assessment of the time series patches by multiple interpreters could provide insight into the magnitude of this error source and this should be considered prior to any practical use of the outputs produced.

Despite the obvious promise of the methods developed in this study, a number of limitations to the proposed procedures remain. As already noted there are numerous error sources that could lead to misleading outputs, some of which can not be quantified without considerable additional effort. These mean that the results should not be used without consideration of the possible consequences of using erroneous data for decision making. Further limitations to the methods include the manual tuning of LT-GEE parameters. Although a reasonable set of parameters were derived in this study these are likely to be specific to our use case and may well benefit from further tuning particularly for monitoring of fine scale invasive conifer spread. Further research is needed to quantify the sensitivity of the approach to early invasions and to invasions into different vegetation types. We believe that this approach produced realistic results for detecting control over large, dense conifer infestations and detected encroachment well once conifer invasions approached canopy closure. However, it should be noted that this method based on medium-resolution satellite imagery is better suited for tracking relatively large scale spread or control activities and where finer scale information is required (e.g. for individual tree detection) other data sources such as manned aircraft or UAV may be more suitable.

With large datasets of this type computing resource must also be considered. In our methodology the original pixel-level segmentation and spectral stabilisation was undertaken using the GEE platform which enables scalable data processing at a sufficient size to cover areas of operational magnitude. Under our current methodology subsequent steps, including raster processing, are undertaken outside of GEE and so computing time becomes more challenging. In the future, efforts attempting to complete more parts of the process within GEE would likely improve performance.

6.7 Conclusion

In this paper we presented the development of a methodology that can make use of the time series Landsat archive to track vegetation changes associated with conifer invasions and their control over a large heterogeneous landscape, dominated by grassland of various types in New Zealand's South Island. The LT-GEE algorithm served as a suitable solution for identifying segments of land cover change across the landscape and for processing the Landsat archive to provide useful outputs for attribution modelling. Subsequently patch-level random forest attribution modelling was successfully used to attribute the causal agent of the changes identified by LT-GEE and used to map invasive conifer spread and control across the study area landscape. Attribution models for invasive conifer control and spread had moderate accuracy and may be used by practitioners with a relevant level of caution.

6.8 Acknowledgements

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6.9 Author contributions

JPD conceived of this study, wrote all software, processed all data, carried out all analysis, and wrote the original draft of the manuscript. All other authors reviewed, edited, and made contributions to the text of the final version.

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6.11 Data accessibility

The Google Earth Engine and R code used to complete this analysis can be accessed at https://github.com/jonathandash/LT-ChangeProc.

Chapter 7

Synopsis

Through the research presented in this thesis three original case studies were conducted that have progressed knowledge of invasive conifer detection using a range of remotely sensed data from satellite, piloted, and unpiloted airborne platforms. In addition to these experimental studies, the current state of knowledge was summarised through two extensive literature reviews. The first, dealing with the detection of invasive plants using remote sensing, and the second systematically summarising the properties of current research into UAV-based IAP detection. This process was critical for formulating the set of research questions that this research sought to answer.

This final chapter provides a synopsis of the research undertaken, highlights the new knowledge developed, identifies the limitations of the research presented, and suggests future research directions.

7.1 Research questions

The following research questions were presented in chapter one:

1. Can ultra-high-resolution data be used to detect the presence of invasive exotic conifers prior to the onset of early coning in a highly vulnerable environment?

2. Can UAV-based models of invasive conifer distribution be transferred between sites and does site complexity have a significant effect on model portability?

3. Given the size and availability of the Landsat archive can automated methods be developed that allow tracking of the historical spread and management of invasive conifers?

These research questions were developed following an extensive literature review and stakeholder engagement. Throughout the synopsis these questions are referenced and the research findings are discussed in light of the new knowledge gained from data collected to answer them.

7.2 Summary of main findings

7.2.1 The current state of remote sensing for invasive plant detection

A comprehensive review of the research literature revealed the state-of-the-art regarding the detection and monitoring of invasive plants using remote sensing. This review revealed an extensive body of literature on the topic and assisted with development of the thesis research questions. Studies originated from throughout the world have used remotely sensed data collected from several platforms (satellite, piloted aircraft, UAV) using various sensors. Analytical methods were various and included a wealth of studies using both object-based and pixel-based analysis. The reported accuracy of published studies was generally very high, this may be influenced by a "publication bias" resulting from the reluctance of authors and journals to publish unfavourable results. The current state of knowledge of the topic was summarised in chapter 2, enabling refinement of method development for this thesis and forming a basis for the subsequent analytical studies.

Specific research gaps identified included the emergence of UAVs as a tool for invasive plant detection, early detection of invasive plants using remote sensing, model transferability, and multi-temporal analysis invasive conifer distributions. Each of these areas was addressed in the following chapters of the thesis, the first through a detailed and systematic review that was published as the first synthesis of the research for this field. The following three areas were addressed through analytical experiments using data collected for this thesis.

Early detection of the presence of invasive plants is of fundamental importance to management efforts because successful control of invasions is reliant on locating and controlling pioneer plants that can colonise new areas through long distance dispersal. Prior to the study undertaken in this thesis no research had attempted to address this gap although it had been identified by stakeholders and researchers as of significant importance (Juanes, 2018).

In a similar manner, the portability of models describing invasive plant distributions between AOIs was identified as a research gap and flagged for further study. This topic had practical applications for all remote sensing studies but was particularly relevant for UAVs where the operator is faced with new decisions during study design that had less impact for more conventional remote sensing.

Although some studies have researched the use of multi-date imagery to detect IAP spread (de Sa et al., 2017) no studies have attempted to deploy quantitative methods based on model fitting through the Landsat time-series stack to automatically identify land cover changes that may be associated with the spread and control of invasive plants. A further notable observation was that there was only a limited amount of research that sought to develop UAVs for invasive plant detection and monitoring and that the studies that had been completed had not been summarised through a dedicated comprehensive review. To address this a comprehensive meta-study of all UAV-based IAP research was undertaken in chapter 3.

7.2.2 The application of emerging technologies to invasive plant detection

The emerging technology of UAVs have matured and now offer a flexible, stable, and cost-effective platform for remote sensing across small to medium sized areas. Chapter 3 provided a structured and comprehensive review and synthesis of all published research undertaken in this field to date and was subsequently published as a peer-reviewed manuscript. The detailed review process was valuable for finessing the research questions addressed in this thesis.

The review revealed that there were 24 published studies into UAV-based IAP research. These originated from throughout the world with the greatest number coming from the USA and China. The studies were based in a wide variety of host environments and encompassed a range of target species and growth forms. This range of applications is testament to the flexibility of UAVs, the variety of threatened environments, and an increasing recognition of the utility of the data that they can provide. Compared to IAP studies using other forms of remote sensing UAV-based studies generally had less focus on trees. This is probably because the finer resolution data available from UAVs enables focusing on smaller and more difficult to detect targets. Where trees were the target growth form for UAV-based studies the research aimed either to detect very small trees prior to reproductive maturity (Dash et al., 2019c) (Chapter 4) or to detect trees in the understorey of indigenous forests (Perroy et al., 2017).

Published IAP research using UAVs is divided evenly between rotary-wing and fixed-wing craft but there has been a definite trend in more recent studies towards the use of commercial rotary-wing craft eschewing fixed-wing or custom-built craft of either configuration. This is probably due to the ubiquity of low-cost and reliable rotary-wing solutions in recent years. Rotary-wing studies tended to be characterised by finer spatial resolution data and the use of more sophisticated sensors than fixed-wing studies. However, the trade-off to this was the area coverage which was significantly larger for fixed-wing craft. This can be explained by the greater aerodynamic efficiency of fixed wing craft that leads to improved battery life and the opportunity for greater area coverage. A wide range of sensors have been deployed (Table 3.2) on UAVs for IAP research but it was notable that the sophisticated and expensive laser scanners and hyperspectral sensors have only been deployed on rotary-wing craft. This is probably due to the improved lift capacity, resilience to turbulent air conditions, and the increased safety of controlled vertical landings. Vertical take-off and landing (VTOL) is a standard feature of rotary-wing craft but is not yet commonly available in all fixed-wing models.

A range of analytical methods were used in the UAV-based IAP research. Both object-based and pixel-based methods were common but only a single study published so far used machine vision methods (Bryson et al., 2010). For pre-processing of UAV data, the Metashape software was the most widely used followed by Pix4D with open source alternatives not yet widely used in UAV-based IAP research. For subsequent processing eCognition was the most popular choice for OBIA and programming languages such as R and Python were also widely used.

A significant finding of this research was that in contrast to the all-platform remote sensing studies the spatial resolution of UAV data was never identified as a limitation in the UAV-based IAP research. This suggests that the properties of the newly available datasets mean that this formerly significant limitation has been solved by the emerging technology. Other limitations persist and frequently cited examples included the limited area coverage, large data size and lengthy processing times, positional accuracy, financial cost of hardware and software, and the lack of suitable field data.

Through a horizon scanning exercise, emerging research or close-to-market solutions that can offer a solution to some of the limitations cited in the existing UAV-based IAP research were identified. These included new craft configurations enabling VTOL in fixed-wing craft and alternative power sources including hydrogen cell batteries, hybrid fuel systems, and in-flight wireless charging. Current legislation is a major limiting factor in many jurisdictions and a modernisation of the rules governing data collection altitude and BVLOS operation are critical to further expanding the range of UAVs to allow for data collection on a more operational scale. In many countries it is likely that the ubiquity of UAVs and their development into serious tools for data collection will give legislators confidence to follow this path. To help facilitate this coalitions of commercial operators and researchers could unite to lobby for progress in this area. Data processing times remain challenging and current bottlenecks will probably be alleviated to some extent by the continued improvement and reduced cost of computing resources. Furthermore, the demand for conventional computing is likely to be reduced by the emergence of new methods based on machine vision that in some instances might be able to process UAV imagery without the need for computationally intensive pre-processing steps such as bundle adjustment and orthomosaic generation.

This research has comprehensively summarised the current state of UAV-based IAP research, factors currently limiting the field, and identified new pathways for research and development that will help guide targeted improvement of the technology. These developments will ensure that UAVs can provide even greater value to researchers and practitioners in the coming years.

7.2.3 The use of UAVs for early detection of invasive conifers

Following the literature review and discussions with stakeholders during the early development of this thesis it became clear that there was an unmet requirement for a remote sensing solution that could detect invasive conifers when they were immature and prior to the onset of coning. This led to the development of RQ1 and resulted in the inception of the study presented in chapter three. This data was particularly desirable for highly vulnerable indigenous and semi-indigenous grass and shrubland that are the dominant land cover across large areas of culturally significant land in the South Island (Figure 6.4). Early detection is critical to preventing colonisation of new areas as identification and control of pioneering individual plants prior to coning onset will reduce or eliminate the seed load transmitted to new areas. The literature review (Chapter 2) showed that significant research effort has been expended to detect and monitor invasions at a broad scale over large areas. Whilst extremely useful for many applications these methods have limited utility for the early detection of new invasions. This is primarily due to the fact that the spatial resolution of the satellite imagery commonly used is too coarse for early detection of such small and scattered targets. The information gathered and summarised in chapter 3 indicated that with appropriate on-board sensors and method development UAVs could provide the ultra-high-resolution data required to meet this demand. The effective range of UAVs and the data collection area that can be covered is currently limited by the development stage of both battery technology and legislation and so another test was designed to determine whether conventional piloted aircraft could be configured to collect data suitable for this task.

A methodology for early detection of invasive conifers in vulnerable, and culturally significant, grassland habitats was designed and tested. The study was located in a dense first order invasion fanning out from a shelterbelt comprised of several *Pinus* species. The invasive trees were large and dense close to the shelterbelt but further away there were scattered individuals of a range of sizes (Figure 4.3). Multispectral and ALS data were collected across this site using both a rotary-wing UAV and a conventional piloted aircraft. An extensive and detailed field dataset was also collected that included records of the tree species, location, dimensions, and coning status. This dataset encompassed more than 17,000 individual trees and has provided a unique and powerful dataset for validation of model accuracy, as well as providing valuable input into numerous research streams outside of this thesis. Multispectral and ALS data were processed to provide rasters detailing the spectral and structural characteristics of the study site. A pixel-based analytical approach was used and the performance of logistic regression and the random forests algorithm for identifying invasive conifers were compared. Both algorithms performed similarly and yielded highly accurate results with almost all trees identified accurately at a tree height of around 2 m. This finding led to the recommendation that logistic regression should be used by practitioners in this scenario. This is because this modelling approach is simpler, easier to interpret, and does not require parameter tuning that might be confusing and time-consuming for practitioners.

Independent validation of the remote detection procedures using the field dataset showed that the methods developed were highly accurate (kappa >0.996) using both the UAV data and the high-resolution data collected from the piloted aircraft. The most accurate models included all available predictors including the ALS data and all available bands from the multispectral imagery. The most important band for classifying invasive conifers was the green band which was clearly suitable for differentiating the dark green vegetation of the invasive conifers from the non-target background vegetation in this environment. Including ALS data in the predictive models led to an improvement in classification performance but this was not as marked as in other research using related methods in a more complex environment (Dash et al., 2017a). Validation using the detailed field dataset showed that detection accuracy was 23% for trees less than 0.5 m, 87% for trees less than 1 m, and nearly 100% accurate when trees were over 2 m in height. The UAV data was useful for accurately detecting trees down to 1 m in height and critically this included 99.3% of the coning individuals in the study area.

This study has provided important new knowledge for the early detection of invasive conifers. This topic has not been specifically addressed by previous research and the study findings indicate that the ultra-high-resolution data provided by UAVs is well-suited to this task. Furthermore, our results showed that with appropriate acquisition settings similar accuracy levels can be achieved using a conventional piloted aircraft. This significantly extends the size of the area of interest that can be captured. However, the flight settings required to achieve the high resolution data required make data acquisition very expensive. Ultimately the best solution might be for periodic piloted acquisitions over a large AOI with regular updates by UAV to check on the progress of an invasion and the efficacy of control efforts initiated. In conclusion, the data collected in this study allow RQ1 to be answered positively within the study environment. In the relatively simplistic setting examined the vast majority of individual trees could be identified prior to the onset of coning.

7.2.4 Understanding the portability of UAV-based invasive conifer distribution models.

Conventional model development using remote sensing requires a labelled reference dataset. Compiling a useful reference dataset can be an expensive and laborious task that typically involves gathering a field dataset or extensive image interpretation. It is possible that that reference datasets could be re-used for a given task but the background conditions of both the donor AOI, used for model development, and the receiver AOI, to which the model will be applied, must be carefully considered. This is particularly relevant to UAV-based data collection because the operator must make a choice about the boundaries of the AOI used for data capture within a given site. If the operator has pre-existing knowledge about the model that will be applied to the data they are collecting and the conditions of the AOI used for model development then they may be able to adjust data collection to improve efficiency and performance. This was the justification that led to RQ2 being investigated in the experiment presented in chapter four.

The hypothesis that UAV-based models of invasive conifer distributions could be transferred to other AOIs without a significant loss of accuracy was tested. This was achieved through an experiment undertaken at three study sites based in vulnerable environments throughout New Zealand. As the interaction between the properties of both donor and receiver AOI was of interest the experiment was designed so that the three sites comprised a complexity gradient of commonly invaded habitats throughout the country. AOI complexity was defined in terms of the ease of data collection and the simplicity of the site that affects how easy the target invasive conifers can be separated from non-target objects. Terrain type and non-target vegetation composition and structure were the principal determinants of site complexity considered. As the capacity for model transfer within, and between, sites was of interest one of the study site included three adjacent but non-overlapping AOIs with relatively similar conditions covered by UAV data.

The experimental results showed that highly accurate models could be produced from the available datasets and that the most accurate models were developed using combinations of multispectral and ALS data. It was found that models could be transferred to different AOIs within a site with very little reduction in model accuracy. The change in model accuracy varied between AOIs and this was probably due to the fact that a single AOI (HFP-3) was moderately steeper and more complex than the others and the UAV imagery for the AOI contained more geometric distortion and mosaicking artefacts than the other two AOIs at this site. Testing model portability between different sites showed that models could be transferred from sites with greater, or equal, complexity to the receiver but not from simpler sites to those that were more complex. Models that included ALS data were the least robust to transfer to different sites and displayed a significant decrease in accuracy when this was attempted. This was because models that use ALS predictors are highly specific to the site conditions encountered during model development. For example, in a simple site ALS data is extremely useful for identifying invasive conifers in an environment with very limited non target shrubs and trees. In contrast within a more complex site the structure of invasive conifers relative to non-target objects contains the most useful information for separation. Models using spectral predictors were the most robust to transfer. This is probably because the spectral properties of the subject invasive conifers are distinct from the surrounding indigenous vegetation encountered in New Zealand. This is more pronounced at simple sites where tussock grasslands form the background vegetation but even in sites with patches of dense indigenous forests (e.g. KFP-1) the dark green colour and near-infrared reflectance of exotic conifers remains distinct.

These results are highly significant for the use of UAV-based models of invasive conifer distributions and provide a robust answer to RQ2. It has been clearly shown that models can be transferred to different AOIs with similar site conditions. This could lead to significant time savings in reference dataset collation and model development effort. The results also indicated that models could be transferred to sites with similar, or simpler, characteristics than the AOI used for model development. This finding has significant implications for UAV survey design for invasive conifer distribution mapping. Although the concepts apply to more conventional remote sensing the UAV use case is particularly relevant because the operator makes an additional decision about where the boundaries of the AOI are defined. With pre-existing knowledge of the model that will be applied the operator can optimise data collection to maximise the stability of models transferred between sites. For example, if a robust model has been developed in a complex AOI this can be applied with some confidence to sites with similar, or less complexity. Of course, the practitioner will need a good understanding of the vegetation conditions throughout the receiver area but in many instances those responsible for data collection have a good understanding of the target site and may have access to pre-existing imagery.

7.2.5 Using the Landsat archive to track the historic spread and control of invasive conifers in New Zealand

Single date remote sensing can only provide information about the current state of the system or landscape under study. Time-series data offers a means of tracking changes that occur over time. This is of fundamental interest from a research perspective but can also help inform land managers and policy makers about the impacts of actions on ecosystem changes. The maturity of long-lived Earth observation missions and the open access data policies mean that the entirety of historical imagery is available for analysis. Significant advances in high performance computing and time-series algorithm development in recent years have meant that the tools are now available to mine this valuable data archive to extract valuable information about landscape scale changes for the first time. Within this paradigm RQ3 was developed. These datasets, computing resources, and algorithms have been proven to provide useful and flexible information on historical land use patterns in many environments but no research had sought to apply these techniques to historical patterns in invasive conifer spread and control.

In chapter 6 the development of a prototype method for tracking the historical spread and management of invasive conifers across a large and heterogeneous landscape covering the majority of New Zealand's South Island was presented. The approach made use of temporal segments identified from the spectral trajectory of pixels in the Landsat time-series image stack identified and processed by the implementation of the LandTrendR algorithm in GEE. The causal agent of these segments was then attributed manually based on time-series image interpretation. Predictor variables extracted from the stabilised spectral trajectory of the change segment were then used to develop a random forest model that could extrapolate the attribution of the causal agent from the model development dataset across the entire 64,000 km^2 study area.

This case study showed that through using the computing capacity and data catalogue of GEE along with the LandTrendR algorithm viable maps showing invasive conifer spread and management could be produced across large and heterogeneous areas. Once the algorithm settings were parameterised for the invasive conifer use case the automated detection of vegetation change through the time series image stack was highly accurate. These segments formed the basis for a secondary classification which was found to be moderately accurate for attributing the causal agent of the vegetation changes produced. Although the overall accuracy for the attribution models was fairly high (Gain OA = 0.86, Loss OA = 0.70) significant inter class confusion remained for the rarer classes including invasive conifer spread and control activity.

Using the methods developed a large scale and coherent maps of invasive conifer spread and control activities across the study area for the period between 2000-2019 was produced. These maps can be useful for managers and policy makers who can cross reference them against historical records of management activities to better understand the consequences of their implementation.

This research answered RQ3 through the implementation of the case study. It was established that the Landsat archive contained useful information on the historical patterns of invasive conifers distribution, suitable algorithms, and modelling techniques were developed to take advantage of this information, and this was implemented on a high performance computing platform.

7.3 Limitations of this research

The research presented in this thesis makes an original and useful contribution to the knowledge of remote detection and monitoring of invasive conifers. However, there are several limitations that either could not be, or were not, addressed that should be noted here.

The literature reviews undertaken for this thesis only incorporated research published in the English language. This is a limitation as it is highly likely that substantial valuable research has been published in other languages.

The results of the study presented in chapter 4 were limited by the fact that the experiment was only carried out at a single site and that site had a very simple vegetation and terrain structure. The simplistic site was actually selected on purpose so that the limits of detection for very small trees and the efficacy of detection prior to the onset of coning could be examined. Nevertheless, due to the simplicity of the site is not possible to ascertain whether the results would be the same in sites with more complex vegetation and terrain characteristics. As with all single site research it is challenging to generalise the findings, however, it should be noted that the vegetation type under study is a hot spot for conifer infestation and dominates large areas of the South Island of New Zealand. It is reasonable to assume that the results of this study are applicable to these areas.

Many UAV studies suffer from geometric distortion and processing artefacts within the imagery used. This was the case in chapter 5 where datasets from different AOIs had differing levels of distortion despite best efforts to minimise this. This is not uncommon and reflects the infancy of the technology, the relatively low cost and miniaturisation of UAV-borne equipment, and the complexity of the image processing problem under study. The results presented in chapter 5 must be viewed with consideration of this factor and, in fact, this was discussed in some length in chapter 5. The use of only remotely sensed data to produce the reference dataset for model development and to identify all areas invaded with the target trees in this study is a further limitation. Field surveys can introduce additional bias and errors, but it is also challenging to produce highly accurate data from aerial imagery alone. This is most evident in more complex environments where target trees may be obscured by non-target trees or shadows or may be confused with other species. Even after taking great care and with multiple technicians spending significant time carefully interpreting imagery some level of error is likely to remain. This error level is impossible to quantify and all remote sensing studies that rely on manual interpretation of aerial imagery are subject to this limitation.

A key outcome of the study presented in chapter 5 was that a multi-site study was installed so that the portability of UAV-based models of invasive conifer distributions could be examined. The study sites were carefully selected to represent a range of vulnerable environments and a site complexity gradient. However, it is important to recognise that these three sites were a sample of a very large and variable population of study sites. The selection of these sites has introduced some observer bias into the study. However, as time and resources are limited all experimenters must make decisions of this type and all reasonable efforts were taken to ensure that the results obtained were as generalisable as possible to a broad range of vulnerable environments within New Zealand. Due to resourcing limitations data from multiple AOIs was only collected at a single site, the site with moderate complexity was chosen to host multiple AOIs. It is possible that more complex sites will have more diverse microsite conditions and so UAV-based models of invasive conifer distributions may be less accurate when transferred to different AOIs within the same site compared to the results reported in chapter 5.

In chapter 6 the analysis focused on the LandTrendR algorithm and found that this was a viable solution to identify spectral segments in the time series Landsat stack that might be associated with invasive conifer spread and control. Numerous other algorithms for detecting changes through time from the Landsat archive have been proposed (Cohen et al., 2017). These include the Vegetation Change Tracker (Diao et al., 2020), Exponentially Weighted Moving Average Change Detection (Brooks et al., 2014), and Continuous Change Detection and Classification (Zhu et al., 2015b). All of these algorithms have properties that make them strong candidates for monitoring historical trends in invasive conifer distributions but LandTrendR was selected for use due to its implementation in GEE and use of a single annual composite, which is advantageous in cloudy environments such as New Zealand. Not trialling the alternative algorithms was a limitation of the work and comparing their performance to LandTrendR should be the focus of future studies.

There were further limitations to the study presented in chapter 6. These included the selection of LandTrendR parameter settings. Despite best efforts to carefully parameterise the algorithm for the use case, it was observed that minor changes to the settings resulted in major changes to the outputs and parameter selection remains a judgement call on behalf of the analyst. However, it is unlikely that this limitation affected the results obtained. The study methodology also relied on the availability of high-resolution time series imagery for interpretation of temporal land cover changes.

Although clearly an exceptionally valuable source of reference imagery this collection is obviously not complete, and some aspects of land cover change could easily have been missed or misinterpreted.

All practicable measures to avoid the deleterious effects of these limitations were taken in this thesis. However, it is clear that some limitations remain and the discussion of these factors here should lead to greater transparency.

7.4 Priorities for future studies

During the development of this thesis a new set of object detection methods were developed and refined by data scientists and have been applied to remote sensing data. Emerging methods such as convolutional neural networks (CNNs) overcome the limitations of conventional pixel-based and object-based methods for object detection in very-high-resolution imagery. These methods could be particularly advantageous for UAV imagery because UAV data is often of a relatively low quality and consistency and so requires specialist processing before metrics such as spectral indices can be reliably calculated (Iqbal et al., 2018; Kelcey and Lucieer, 2012). Conventional OBIA approaches have not been able to fully exploit the additional information available in the higher level of spatial detail provided by UAV imagery (Blaschke, 2010).

State-of-the-art CNN models are typically trained using very large, labelled reference datasets, provide highly accurate object detection, and are becoming widely embedded in many technologies where they are frequently referred to as deep learning algorithms. Using these approaches image segmentation and classification has seen a step change in fields such as medical diagnostics, where accuracy levels approach and even exceed human image interpretation (An and Liu, 2019; Lundervold and Lundervold, 2019; Yadav and Jadhav, 2019), and for the detection of invasive animals (Dayoub et al., 2015). CNN algorithms are beginning to be applied to the field of remote sensing for applications such as species mapping (Kattenborn et al., 2019a, 2020), land use classification (Zhang et al., 2019), and have been applied to seedling counting in tree nurseries using UAV data (Fromm et al., 2019).

It seems likely that these CNN algorithms will be applied to invasive plant detection research in the near future. To facilitate this a substantial research effort is required to understand how best to acquire the large labelled reference datasets, and how to apply the algorithms using UAV data at scale. CNN models are typically deployed using powerful graphical processing units (GPU) and further software development effort will be required to provide usable solutions for researchers and managers to make use of these cutting-edge developments. Further research is also required to better understand how errors propagate through CNN-based solutions, how error rates compare to alternative methods, and how generalisable and portable CNN-based models are to a range of background conditions.

The UAV-based research conducted for this thesis omitted hyperspectral imagery. This is because of budgetary constraints and limited availability of proven commercial hyperspectral imagers designed for UAVs during the development of this research. The market for 'snapshot' style hyperspectral cameras designed for use with UAVs has matured rapidly in recent years and these systems have been deployed for invasive plant mapping e.g. (Kattenborn et al., 2019b). This datatype requires some degree of data reduction and a somewhat different approach to analysis due to the large number of often closely correlated spectral bands. Hyperspectral sensors offer a finer spectral resolution than the multispectral cameras used in the UAV case studies in this research. This characteristic is clearly valuable for differentiating some IAPs in some more complex environments but in the case of invasive conifers in New Zealand the spectral properties of the target vegetation is quite different to the indigenous vegetation in most environments and so the multispectral cameras used in this research is adequate for spectral differentiation and are available at a significantly lower cost. For this reason, it is unlikely that the use of hyperspectral cameras would have significantly changed the results obtained although accuracies may have been higher for models in the more complex sites. It may also be true that the results reported could be considerably more generally applicable with a hyperspectral camera as data from these devices may be more suited to IAP detection in settings where the target plant is less distinct in the near-infrared wavelengths. Future research should deploy UAV-based hyperspectral cameras for invasive plant detection in New Zealand. This research could test whether and in what context there is advantage to using hyperspectral imagery. This will guide researchers and practitioners considering purchasing different sensor hardware options.

Such a large and varied area (ca. 2 M ha) within New Zealand is affected by invasive conifers, and various information demands it is clear that any single data source cannot provide a complete solution for detection and monitoring. In recognition of these facts, methods exploiting various platforms (satellite, piloted aircraft, and UAV) and a range of sensors were researched. Each sensor-platform combination has properties that can offer information on invasive conifer distribution at different scales, accuracies, and for a variety of applications. However, techniques that link different remotely sensed data sources can provide enhanced knowledge of the host environment and the distribution of the target plants. This linkage usually takes one of two forms, either the remotely sensed datasets are merged to provide a dataset with greater information content than either of the constituent parts, or one dataset is used to provide input to a second so that the understanding gained can be distributed further. In this thesis the first approach was examined by fusing datasets of different types but not the second. In the context of invasive plant detection this has been researched previously by using UAV data as an input to satellite-based mapping of invasive conifer distributions

(Kattenborn et al., 2019b). As the results of this study show this is undoubtedly a useful approach that is highly relevant for our use case. Future research should focus on expanding the methods outlined in Kattenborn et al. (2019b) and testing the efficacy of this approach in a range of environments and using various datasets with different error structures. In this manner large scale maps can be produced that take advantage of the beneficial properties of the constituent datasets. For example, highly accurate UAV-based distribution maps such as those developed in chapter 5 could be used as inputs to satellite imagery based maps for large scale mapping. Further research is required to understand how errors propagate through maps developed in this manner.

Much of the research presented within this thesis has focused on the development of UAVs as a tool for invasive conifer detection and monitoring. However, to provide information across large areas Earth observing satellites remain the only viable option. Furthermore, monitoring historical trends requires data from long-standing data archives from Earth observing missions. For this reason, data extracted from the Landsat archive was investigated to monitor invasive conifer spread and control rates across large areas of New Zealand. This powerful dataset was analysed using the HPC framework of Google Earth Engine and was found to be a valuable resource for monitoring changes back to the year 2000. However, it should be noted that a wide range of other commercial and government managed satellite data sources are also available. Many of these have finer spatial, spectral, and temporal resolutions than Landsat although the longevity of the Landsat missions provides a uniquely long and dense time-series. Given the high costs of acquiring commercial satellite imagery open access datasets are more appealing although significant previous research has used both data sources for monitoring invasive plants e.g. (Underwood et al., 2003). The Sentinel satellites which are part of the ESA's Copernicus mission deserves special mention here as they can be accessed without financial cost and have higher spatial resolution than the current incarnation of Landsat. ESA's Sentinel satellites now offer a sophisticated and stable data product with global coverage and rapid return interval to New Zealand. Should a national invasive conifer mapping effort be undertaken in the near future this product would be a highly suitable candidate.

7.5 Concluding remarks

This thesis summarises a range of research that has been been completed to address the challenge of remote detection of invasive conifers. Three experiments located across multiple sites using a range of platforms were installed and used to provide new knowledge and insights into several aspects of method development and deployment. The three research questions identified in chapter one have been examined through new data collection and the installation of several targeted case studies. The detection and monitoring of invasive conifers is a challenging and important task that has a vital role to play in safeguarding New Zealand's ecological, economic, and social wellbeing. The research presented in this thesis hopefully goes some way towards providing a viable solution to this important challenge.

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